Comparison of Different Modelling Techniques

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March 1998

Dedicated To

Lord Samba Sada Shiva

Dedicated To

Lord Samba Sada Shiva

CERTIFICATE

This is to certify that the work contained in the thesis entitled "**Comparison of Different Modelling Techniques**" by Mr. V. Sharat Chandra has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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ABSTRACT

The methods of modeling studied in the present work include fuzzy least square regression, cluster wise fuzzy regression, fuzzy auto regressive moving average(ARMA) method, Sugeno-type fuzzy system identification technique and orthogonal parameter estimator embedded with fuzzy discretization (ortho-clustering) technique. Fuzzy least square regression with its four variations are developed. The effect of different modeling functions upon the performance of the fuzzy regression is evaluated. Cluster wise regression is used mainly to deal with the heterogeneity of the observed data. The effect of different clustering algorithms upon the performance of the cluster wise regression is evaluated. The simple fuzzy regression method is applied to the ARMA technique for modeling a dynamical system. Sugeno-type fuzzy identification technique is developed to include the fuzzy reasoning and implications in modeling of the system. The premise parameters and consequence parameters identification is separated through ortho-clustering technique and the effect of different clustering methods on its performance is evaluated. The above algorithms are applied to the problems of estimation of life of converter lining and modeling of Box Jenkins'gas furnace for evaluating their performance. A comparison of performance of all the developed methods is brought out from the results of the two test problems. The test problems are also modeled through neural networks and results are presented for comparison purpose. The performance of cluster wise fuzzy regression is the best of all the other techniques for modeling a system having inherent imprecision and/or having very few data to describe the system, where as for a simple system like Box Jenkins' gas furnace cluster wise conventional regression has better performance.

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Chapter 1

INTRODUCTION

Modeling is the process of establishing a functional relationship among the dependent and independent variables of the system. There are a number of techniques available for system modeling, but their application depends on the nature of the system to be modeled. For example, auto regressive moving average technique is used in modeling a time series or a dynamical system. For modeling a static system, conventional regression is used, where as probabilistic methods are used for a system including random errors. Similarly to model a system described by very few data and/or imprecise data, fuzzy system modeling techniques are used. The major part of the thesis is devoted to evaluate the performance of various fuzzified models for a given modeling technique. A comparison between conventional and fuzzified methods have been presented. The measure of performance is considered to be mean error, mean square error, root mean square error, standard deviation of error, maximum error, minimum error, slope(ratio of predicted to the actual) where error is given by the difference of actual value to the predicted value.

1.1 Brief review of modeling methods

The present section discusses the advantages and shortcomings of the following methods of modeling whose performance is evaluated in the present thesis.

i. Fuzzy Least square regression modeling

In Diamond [1], several models are proposed as fuzzy analogues of simple linear least squares, and use fuzzy data to compute the parameters. Equations are derived which are rather similar to the normal equations of classic least squares for single input and single output system. In this approach, the solution of the least square optimization problem depends on the sign of the coefficient parameter of the model and proposed method finding solution is very particular to the single input system where the cases arise are only two. But the extension of the same to multi input systems needs heavy computation as the cases are 2^n where n is the number of input variables.

ii. Cluster wise regression modeling

The regression analysis in the case of heterogeneity of observations is commonly presented in practice. To handle the problem of heterogeneity, the observations are clustered using a suitable technique and then their membership values are used as weights in the weighted least square estimation. This approached is proposed in Yang and Ko[2]. Disadvantage of this method is that the results heavily depend on the chosen clustering algorithm.

iii. Auto regressive moving average (ARMA) modeling

ARMA class of models, developed by Box and Jenkins [3]has become one of the most popular time series forecasting models. To simulate and predict a time series, it is modeled as the output of the dynamic system whose input is white noise. Such a model can be described in several ways, but if *parsimonious parameterization* is required then ARMA model is employed. The conventional ARMA has the inability to model the imprecise and ambiguous data. This problem is dealt in detail in this thesis.

iv. Sugeno-type Fuzzy Identification Method

The fuzzy model suggested by Takagi and Sugeno [4]in 1985 can represent or model a general class of static or dynamic nonlinear systems. It is based on "Fuzzy partition" of input space and it can be viewed as the expansion of piecewise linear partition is represented as

$$R^i : \text{If } x_1 \text{ is } A_1^i \text{ and } x_2 \text{ is } A_2^i \text{ ...., and } x_m \text{ is } A_m^i$$

$$\text{then } y^i = a_0^i + a_1^i x_1 + \ldots\ldots + a_m^i x_m \qquad \ldots\ldots\ldots\ldots\ldots(1.1)$$

$$\hat{y} = \frac{\sum_{i=1}^{c} w^i y^i}{\sum_{i=1}^{c} w^i}, \qquad w^i = MIN_{J=1}^{M} A_j^i(x_j) \qquad \ldots\ldots\ldots\ldots\ldots(1.2)$$

where R^i (i=1,2,.....,c) denotes the i^{th} fuzzy rule, and X_j(j=1,2,.....m) is the input and y^i is the output of the fuzzy rule R^i. For simplicity, a system with, multi-input and single output (MISO) is assumed. In the case of a multi-output system, several output variables such as y_1^i and y_2^i are used. $A_1^i, A_2^i, \ldots\ldots, A_m^i$ are fuzzy variables with bell-typed, trapezoidal, triangular, or other membership functions representing a fuzzy subspace in which the implication R^i can be applied for reasoning. From Eq. 1.1 and Eq. 1.2, it is noted that Takagi and Sugeno's fuzzy model approximates a nonlinear system with a

combination of several linear systems by decomposing fuzzily the whole input space into several partial spaces and representing each input/output (I/O) space with each linear equation. In [4], the identification of the fuzzy model described in Eq. 1.1 is carried out iteratively in the following way: first, premise parameters are assumed, then consequent parameters are optimally adjusted with respect to the given premise parameters, and then the premise parameters are adjusted iteratively by complex algorithm, a nonlinear optimization method. However, implementing such an algorithm seems not an easy exercise[5], because the problems of determining the optimal membership variables involve a nonlinear programming problem.

v. Orthogonal parameter estimation technique (Ortho-Clustering Method)

The basic idea of orthogonal parameter estimator [5] is to separate the premise identification from the consequence identification, while these are mutually related in the Sugeno-type model. The separation of the premise identification from the consequence identification is a significant advantage of the proposed modeling approach, because it can greatly simplify the process of building a Sugeno-type model. In this approach, the premise of the model is first determined using a fuzzy discretization technique by constructing reference fuzzy sets. This amounts to the partition of the input space. The number of reference fuzzy sets determines the number of rules and number of linear equations in the consequent part of the model. The parameters of these linear equations are then estimated using an orthogonal estimator.

For determining the reference sets, the data are classified using suitable clustering algorithm. The chosen clustering algorithm plays an important role in the division of input space, hence the performance of the estimator. The proposed method does not evaluate the effect of clustering method upon the performance of the model.

1.2 Description of clustering methods used

This section presents a brief idea about various clustering algorithms used in cluster wise regression and orthogonal parameter estimation, for evaluating the effect of classification method upon the performance of each model. The detailed explanation about the implementation of these methods is given in [14].

i. Fuzzy c-means clustering

This method uses concepts in n-dimensional Euclidean space to determine the geometric closeness of data points by assigning them to various clusters or classes and then

combination of several linear systems by decomposing fuzzily the whole input space into several partial spaces and representing each input/output (I/O) space with each linear equation. In [4], the identification of the fuzzy model described in Eq. 1.1 is carried out iteratively in the following way: first, premise parameters are assumed, then consequent parameters are optimally adjusted with respect to the given premise parameters, and then the premise parameters are adjusted iteratively by complex algorithm, a nonlinear optimization method. However, implementing such an algorithm seems not an easy exercise[5], because the problems of determining the optimal membership variables involve a nonlinear programming problem.

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This method uses concepts in n-dimensional Euclidean space to determine the geometric closeness of data points by assigning them to various clusters or classes and then determining the distance between the clusters.

K-mean clustering algorithm finds a set of cluster centers and partitions the training data into subsets. For the sake of continuity, the subsets overlap to a limited extent. Each cluster center is associated with one of the hidden units (h) in the network. The data are partitioned such that the training points are assigned to the cluster with nearest center.

iii. Self Organizing Map (SOM)

Kohenon network performs clustering through a competitive learning mechanism called "winner takes all". In essence, the node with largest activation level is declared the winner in the competition. This node is the only node, suppressed to the zero activation level. Furthermore, this node and its neighbors are the only nodes permitted to learn for the current input pattern. After training, the weight vector of each node encodes the information of a group of similar input patterns. Given an input vector, it is assigned to the node with the maximum activation. Since the number of nodes is fixed, the net algorithm is similar to the K-means clustering algorithm.

iv. Adaptive resonance theory (ART2)

ART2 is widely used clustering technique for analog or continuous valued patterns. The patterns are classified or clustered with the accuracy defined by a factor called "vigilance factor". Their ability to generalize is limited; however, the ability of this network to create new pattern class in its knowledge base on the arrival of novel pattern makes it very suitable for clustering. The classification is dependent on the presentation of input patterns.

v. Fuzzy ART

Fuzzy ART, can classify both binary and analog valued patterns. In this network also, the clustering is mainly dependent on the factor called vigilance factor and order of presentation of input patterns also plays role in classification. This is also an unsupervised network, because one need not to specify number of clusters. This is determined by the network itself depending upon the vigilance factor

1.4 Problem statement

Main emphasis of this work is to compare the performances of different modeling techniques. Here we propose a new approach to fuzzy least square method for multi input system which overcomes the disadvantage of Diamond[1] method as mentioned before. The effect of modeling functions upon the performance of the model is studied. We develop Fuzzified models of ARMA and cluster wise regression by applying the fuzzified

least square regression to their conventional models. The effect of different clustering methods on the performance of orthogonal parameter estimator and cluster wise regression model is evaluated. Also Sugeno-type fuzzy identification method is implemented.

1.5 Test System description

In the present work two problems are considered for evaluating the performance of the developed models viz. estimation of life of converter lining and modeling of Box Jenkins' gas furnace.

1.5.1 Estimation of life of converter lining problem

The life of steel making converter lining can be expressed in terms of number of heat runs. This number of heat runs can be considered to be a function of 30 variables namely Hot metal weight HM C, Silicon in hot metal, Mn in hot metal, S in hot metal, P in hot metal, temperature of hot metal, weight of the scrap present in hot metal, duration of the blow, quantity of blow O_2, IST, tap temperature, tap to tap time, presence of slag coating, quantity of lime added, ore, Dolo, Lance ht., bath C, bath Mn, bath Si, bath S, bath P, slag basicity, %FeO, %MgO, %SiO_2, %CaO, %MnO, hot metal to scrap ratio. The data set for these 30 variables is collected for 15 campaigns. Various dimensionality reduction techniques have been applied and the experience of R&D of SAIL is also taken into account to model the converter life with reduced number of variables.

i. Estimation of life converter lining problem (ICA)

Through ICA (independent component analysis) the following 13 variables are selected as inputs and life of converter lining in terms of heat runs as out put[14]. The input variables selected are mean hot metal temperature, mean blow O_2, mean tap to tap temperature, mean lime added, mean ore, mean bath C, mean bath S, mean bath P,mean basicity of slag, mean %FeO, mean %MgO, mean %CaO, mean %MnO. The data are given in Table 1.1

ii. Estimation of life converter lining problem (PCA)

Through PCA (principal component analysis) the following 13 variables are selected as inputs and life of converter lining in terms of heat runs as out put [14]. The input variables selected are mean hot metal temperature, mean Si in hot metal, mean Mn in hot metal, mean blow O_2, mean tap to tap temperature, mean tap to tap time, mean lime added mean ore, mean bath C, mean bath S, mean bath P, mean basicity of slag, mean %FeO, mean %CaO. The data is given in Table 1.2.

iii. Estimation of life converter lining problem (mean, R&D)

Through experience of RDCIS group, the following 13 variables are selected as inputs and life of converter lining in terms of heat runs as out put.[14] The input variables selected are mean ratio of hot metal to (hot metal + scrap), mean Si in hot metal, %Si in hot metal greater than equal to 1.1, mean Mn in hot metal, mean blow O_2, mean tap to tap temperature greater than or equal to 1700, mean tap to tap time greater than are equal to70 minutes, %presence of slag coating, mean lime added, %C in steel less than or equal to 0.05, %basicity of slag less than or equal to 2.5, %FeO greater than or equal to 22, mean MgO in slag. The data is given in Table 1.3.

iv. Estimation of life converter lining problem (median, R&D)

Through experience RDCIS group, the following 11 variables are selected as inputs and life of converter lining in terms of heat runs as out put. The input variables selected are median of ratio of hot metal to (hot metal + scrap), median Si in hot metal, median Mn in hot metal, median blow O_2, median tap to tap temperature, median tap to tap time, median lime added, median %C in steel, median %basicity of slag, median %FeO, median MgO in slag [14]. The data is given in Table 1.4.

In order to decide the model parameters so as to make the model convergent with as many samples as possible, it was decided to train the model with 13 samples of input out put combinations. Testing was done with 2 samples of input combination to predict the life of the converter lining. The output was compared with the actual life of the converter lining to evaluate the performance of the fitted model.

1.5.2 Modeling of Box Jenkins' gas furnace data

In the present work, Box and Jenkins' gas furnace data is used [3]. The data consist of 296 I/O measurements of a gas furnace system: the input measurement $u(k)$ is gas flow rate into the furnace and the output measurement is CO_2 concentration in out let gas. The sampling interval is 9 seconds. For comparison with conventional fuzzy models, $u(k)$, $u(k-1)$, $u(k-2)$ and $y(k-1)$, $y(k-2)$, $y(k-3)$ are chosen as the variable of the fuzzy model. The data are given Table 1.5

1.6 Organization of thesis

Fuzzy least square regression including its four variations and conventional least square regression (variation 5), cluster wise regression and ARMA techniques are discussed in chapter 2. Sugeno-type fuzzy system identification and orthogonal parameter estimation (ortho-clustering) techniques are discussed in chapter 3. Results of each modeling

technique with respective to two problems of estimation of life converter lining and modeling of Box Jenkins' gas furnace are discussed in the same section where the respective modeling method is described in detail. A comparison of performance of each modeling method is brought out in chapter 4. Finally the conclusions and future scope of the work is presented in chapter 5.

Chapter 2

2.1 Fuzzy least square regression modeling

2.1.1 Introduction

Regression analysis is used in evaluating the functional relationship between the dependent and independent variables also in determining the best-fit model for describing the relationship. In the usual conventional model the deviations between the observed values and the estimated values are supposed to be due to measurement errors or random variations. But sometimes the deviations are due to the mprecise observed data or the indefiniteness of system structure. In this case the uncertainty is not due to randomness but fuzziness. Regression analysis on fuzzy data in dealing with fuzziness is usually called Fuzzy Regression Analysis.

Tanaka et al. [6] first proposed this study in linear regression analysis with the fuzzy model. They considered the linear fuzzy regression model$Y=A_1x_1+\dots+A_p x_p$ where the parameters A_1 ,.....,and A_p are triangular fuzzy numbers and the independent variables x_1, ... , x_p are real-valued numbers. Then they transformed the optimization problem of estimation to the linear programming problem. Based on this approach, Tanaka et al. [7], [8] and Ishibuchi et al. [9] continued research in this area. A generalization of the Tanka approach for the general form of regression equations about LR-type fuzzy numbers, is developed by Bardossy [10].

We note that the Tanaka approach is quite complicated in solving the optimization problem. It is unclear what the relation is to a least-square concept. The measure of best fit by residuals is not presented in the Tananka approach. Therefore, Diamond [1] proposed the so-called fuzzy least squares. Based on a metric d_f on the space $F(\mathbf{R})$ of all fuzzy numbers Diamond gave a metric d on the space F(R) by

$$d^2[X_1 \cdot X_2] = \left\{(x_1 - x_2)^2 + (x_1 - x_2 - (\alpha_1 - \alpha_2))^2 + (x_1 - x_2 - (\beta_1 - \beta_2))^2\right\}$$

(1) Fuzzy input and fuzzy output

$$\tilde{Y} = a + b\tilde{X} \quad \text{where } a, b \in R, \quad \tilde{X} \in F_T(R)$$

and

$$\tilde{Y} = \tilde{A} + b\tilde{X} \quad \text{where } b \in R, \quad \tilde{A}, \tilde{X} \in F_T(R),$$

(2) numerical input and fuzzy output

$$\tilde{Y} = \tilde{A} + \tilde{B}x, \qquad \text{where } x \in R, \quad \tilde{A}, \tilde{B} \in F_T(R)$$

where $F_T(R)$ is a fuzzy space.

the corresponding least square optimization problems are

$$\text{minimize } r(a,b) = \sum_{i=1}^{n} d^2\left(\tilde{Y}_i, a + b\tilde{X}_i\right); \qquad \text{....(2.1)}$$

$$\text{minimize } r(\tilde{A}, b) = \sum_{i=1}^{n} d^2\left(\tilde{Y}_i, \tilde{A} + b\tilde{X}_i\right); \qquad \text{....(2.2)}$$

$$\text{minimize } r(\tilde{A}, \tilde{B}) = \sum_{i=1}^{n} d^2\left(\tilde{Y}_i, \tilde{A} + \tilde{B}x_i\right); \qquad \text{....(2.3)}$$

From the Eq 2.1 and Eq 2.2 it can be clearly seen that the function to be minimized depends on the sign of the coefficient parameter of each input of the model, thus giving rise to different solutions for different cases. In Diamond [1] the proposed method finding solution is very particular to the single input system where the cases arise are only two. But the extension of the same to multi input system needs heavy computation as the cases are 2^n where n is the number of input variables.

The technique presented in the present work overcomes this problem for multi input single output system modeling. In addition to that the effect of different modeling functions upon the performance of each model is studied. Developed models are applied to the problems of estimation of life of converter lining and Box Jenkins' gas furnace modeling and the results were discussed in the section 2.1.4.

2.1.2 Formulation of Simple Fuzzy Least Squares problem

The formulation of the method is based on the use of L-R fuzzy numbers (see Appendix) and their very simple form of distance $d[.,.]^2$,and reduces the problem to that of finding the minimum of a classical function. The fuzzy numbers of type L-R constitute a

special class of fuzzy numbers very useful in estimation and other applications. Specifically, a fuzzy L-R number M has a membership function of the type

$$\mu_M(x)=\begin{cases}L((m-x)/\alpha),..x\le m\\ R((m-x)/\beta),..x\ge m\end{cases}$$

where m is a classical number, α and β are parameters, and L(.), R(.) are functions of special type (Satisfying the condition of Def.A.1 in the Appendix). Symbolically an L-R fuzzy number M is denoted by:

$$M=(m,\alpha,\beta)$$

Let F(R) be the set of all fuzzy L-R numbers that are defined on R. On the set F(R) one can define a linear structure and a norm $d[.,.]^2$ which is the distance of two fuzzy L-R numbers $X_1=(x_1,\alpha_1,\beta_1)$ and $X_2=(x_2,\alpha_2,\beta_2)$ can be determined .

$$d^2[X_1-X_2]=\{(x_1-x_2)^2+(x_1-x_2-(\alpha_1-\alpha_2))^2+(x_1-x_2-(\beta_1-\beta_2))^2\}$$

as given in [11]. Let Y is the output vector of m number of samples and X_j is the vector of m samples of j^{th} input variable, n is the number of input variables. Considering the three simple fuzzy regression models as in Diamond [1] and applying them to the case of multi input single output system gives rise to the following models

(1)Fuzzy input and fuzzy output

(F1): $\quad \tilde{Y}=a_0+\sum_{j=1}^{n}a_j\tilde{X}_j \quad$ where $a_0,a_j\in R,\ \ \tilde{X}_j\in F_T(R),\ \ j=1,2,\dots n$

and

(F2): $\quad \tilde{Y}=\tilde{A}_0+\sum_{j=1}^{n}a_j\tilde{X}_j \quad$ where $a_j\in R,\ \ \tilde{A}_0,\tilde{X}_j\in F_T(R),\ \ j=1,2,\dots n$

(2) Crisp input and fuzzy output :

Suppose that data pairs $x_{i,j}$, $\tilde{Y}_i$ i=1,2,..m and j=1,2....n are observed, where the real numbers $x_{i,j}$ are non-negative and each $\tilde{Y}_i$ is fuzzy. The model can be defined by

$\tilde{Y}=\tilde{A}_0+\sum_{j=1}^{n}\tilde{A}_jX_j$, $\quad$ where $X_j\in R$, $\ \tilde{A}_0,\tilde{A}_j\in F_T(R)$

2.1.3 Solution of fuzzy least square problem : Fuzzy input and fuzzy output

variation 1: (F1) $\tilde{Y} = a_0 + \sum_{j=1}^{n} a_j \tilde{X}_j$ where $a_0, a_j \in R$, $\tilde{X}_j \in F_T(R)$, j=1,2,....n and

variation 2: (F2) $\tilde{Y} = \tilde{A}_0 + \sum_{j=1}^{n} a_j \tilde{X}_j$ where $a_j \in R$, $\tilde{A}_0, \tilde{X}_j \in F_T(R)$, j =1,2,....n

Each is to be fitted to the data in the sense of best fit with respective to the d^2_{LR}-metric. Clearly (F2) mildly generalizes (F1).

In association with the model (F2), formulated as follows

variation 1:fuzzy parameters with fuzzy input

Solution of fuzzy least square problem comprises essentially the following steps

Step (i) : Preprocess or transform (scale) the data.

Step (ii) : Fuzzify the input and output (if necessary)

Step (iii) : Initialize the model parameters

Step (iv) : Initialize s, s' terms

Step (v) : Evaluate the classical function basing on d^2_{LR} metric

Step (vi) : Get the simultaneous equations by partially differentiating the classical function with respective to each parameter.

Step (vii) : Solve the simultaneous equations to get the model parameter

Step (viii) : Evaluate the stopping criterion

Step (ix): Till the criterion is satisfied repeat the steps (iii) to (viii)

Details of each of the step are as follows :

Step (i) Data Preprocessing

Performance of the model is sensitive to the scaling of the data. So the data is scaled between X_{low} and X_{high} with the formula

$$X_{scaled} = X_{low} + (X_{high} - X_{low}) \frac{(X_{unscaled} - X_{min})}{(X_{max} - X_{min})}$$

where X_{min} and X_{max} are the minimum and maximum of the data to be scaled, $X_{unscaled}$ is the raw value, X_{scaled} is the normalized value. From numerous experiments, it is suggested that input should be scaled between 0 and 1.0 to obtain the better performance.

Step (ii) Fuzzification of data (if necessary)

If the data available is crisp then for the analysis, it is fuzzified using a suitable fuzzification method. The fuzzification method used in the thesis is given in Appendix. If the data is already in the fuzzified form then this step is avoided.

Step (iii) Initialization of model parameters

With conventional regression analysis, the model parameters are initialized before actually analyzing through fuzzy regression modeling.

Step (iv) initialization of s, s' terms

From the model defined as below

$$\tilde{Y} = \tilde{A}_0 + \sum_{j=1}^{n} a_j \tilde{X}_j \qquad \text{where } a_j \in R,\quad \tilde{A}_0, \tilde{X}_j \in F_T(R),\quad j=1,2,\ldots n$$

i.e.

$$\tilde{Y}_i = \tilde{A}_0 + \sum_{j=1}^{n} a_j \tilde{X}_{ij} \qquad i = 1,2,\ldots\ldots m.$$

The product of a_j, $X_{i,j}$ is defined differently if $a_j > 0$ or $a_j<0$ the formulation of the least-squares optimization problem is dependent upon the sign of coefficient parameter of each input variable. To overcome the difficulty in evaluating the metric as described in the section 2.1.1, a generalized approach is proposed by introducing new variables. Let s_j, s'_j be two variables whose value is updated according to the sign of the coefficient a_j where $j=0,1,\ldots n$.

i.e.

$s_i = 1$ and $s_i' = -1$ if i^{th} coefficient parameter sign is positive

$s_i = -1$ and $s_i' = 1$ if i^{th} coefficient parameter sign is negative

Step (v) : Evaluation of classical function

The distance measure is evaluated as

(M1): minimize $r(a_j) = d_{LR}^2$ where d_{LR}^2 is given by

$$d^2_{LR} = \sum_{i=1}^{m} d^2\left[\left(\left(a_{m_0} + \sum_{j=1}^{n} a_j x_{m_{ij}}\right), \left(a_{\alpha_0} + \sum_{j=1}^{n} a_j x_{\alpha r_{ij}}\right), \left(a_{\beta_0} + \sum_{j=1}^{n} a_j x_{\beta r_{ij}}\right)\right), \tilde{Y}_i\right]$$

where

$x_{\alpha r_{ij}} = \left(s_i x_{\alpha_{ij}} +\right.$

$x_{\beta r_{ij}} = \left(s_i x_{\beta_{ij}} +\right.$

thus the classical function is

$$d^2{}_{LR} = \sum\left\{\left(a_{m_0} + \sum_{j=1}^{n} a_j x_{m_{ij}} - y_{m_i}\right)^2 + \left(\left(a_{m_0} + \sum_{j=1}^{n} a_j x_{m_{ij}} - y_{m_i}\right) - \left(a_{\alpha_0} + \sum_{j=1}^{n} a_j x_{\alpha r_{ij}} - y_{\alpha_i}\right)\right)^2\right.$$

$$\left.+\left(\left(a_{m_0} + \sum_{j=1}^{n} a_j x_{m_{ij}} - y_{m_i}\right) - \left(a_{\beta_0} + \sum_{j=1}^{n} a_j x_{\beta r_{ij}} - y_{\beta_i}\right)\right)^2\right\} \qquad \text{.......(2.4)}$$

Step (vi) : Partial Differentiation of Classical Function

The parameters a_j where j=0,...n can be determined by classical minimization of the real valued function. Partially differentiating the classical function with respective to each parameter of the model

$$\text{Parameter } a_l : \quad \frac{\partial d_{LR}}{\partial a_l} = 0 \qquad \text{...(I)}$$

$$\text{Parameter } a_{m_0} : \quad \frac{\partial d_{LR}}{\partial a_{m_0}} = 0 \qquad \text{....(II)}$$

$$\text{Parameter } a_{\alpha_0} : \quad \frac{\partial d_{LR}}{\partial a_{\alpha_0}} = 0 \qquad \text{....(III)}$$

$$\text{Parameter } a_{\beta_0} : \quad \frac{\partial d_{LR}}{\partial a_{\beta_0}} = 0 \qquad \text{....(IV)}$$

By partial differentiation of the classical function, the resulting algebraic system of n+3 equations in the n+3 unknowns are as follows

Eq. (I) results the following n equations

$$\sum\left\{\left(x_{m_{il}}\right)\left(a_{m_0} + \sum_{j=1}^{n} a_j x_{m_{ij}} - y_{m_i}\right) + \left(x_{m_{il}} - x_{\alpha r_{il}}\right)\left(\left(a_{m_0} + \sum_{j=1}^{n} a_j x_{m_{ij}} - y_{m_i}\right) - \left(a_{\alpha_0} + \sum_{j=1}^{n} a_j x_{\alpha r_{ij}} - y_{\alpha_i}\right)\right)\right.$$

$$\left.+\left(\left(x_{m_{il}} - x_{\beta r_{il}}\right)\left(a_{m_0} + \sum_{j=1}^{n} a_j x_{m_{ij}} - y_{m_i}\right) - \left(a_{\beta_0} + \sum_{j=1}^{n} a_j x_{\beta r_{ij}} - y_{\beta_i}\right)\right)\right\} = 0$$

where $l = 0,1,\ldots\ldots n$. ....(2.5)

Eq. (II) results the following equation

$$\sum\left\{\left(a_{m_0}+\sum_{j=1}^{n}a_jx_{m_{ij}}-y_{m_i}\right)+\left(\left(a_{m_0}+\sum_{j=1}^{n}a_jx_{m_{ij}}-y_{m_i}\right)-\left(a_{\alpha_0}+\sum_{j=1}^{n}a_jx_{\alpha r_{ij}}-y_{\alpha_i}\right)\right)\right.$$
$$\left.+\left(\left(a_{m_0}+\sum_{j=1}^{n}a_jx_{m_{ij}}-y_{m_i}\right)-\left(a_{\beta_0}+\sum_{j=1}^{n}a_jx_{\beta r_{ij}}-y_{\beta_i}\right)\right)\right\}=0 \qquad \ldots\ldots.(2.6)$$

Eq. (III) results the following equation

$$\sum_{i=1}^{m}\left(\left(a_{m_0}+\sum_{j=1}^{n}a_jx_{m_{ij}}-y_{m_i}\right)-\left(a_{\alpha_0}+\sum_{j=1}^{n}a_jx_{\alpha r_{ij}}-y_{\alpha_i}\right)\right)=0 \qquad \ldots\ldots..(2.7)$$

Eq.(IV) results the following equation

$$\sum_{i=1}^{m}\left(\left(a_{m_0}+\sum_{j=1}^{n}a_jx_{m_{ij}}-y_{m_i}\right)-\left(a_{\beta_0}+\sum_{j=1}^{n}a_jx_{\beta r_{ij}}-y_{\alpha_i}\right)\right)=0 \qquad \ldots\ldots..(2.8)$$

Step (vii) Solution to the simultaneous equations

These equations are solved in a straightforward way using matrix inversion technique and the parameters of the model are obtained.

Step (viii) Evaluation of the stopping criterion

The new parameters are compared with the old parameters and the process is stopped when the new parameters are sufficiently close enough to old parameters i.e.

max $|a_j(count)-a_j(count-1)|<\varepsilon$ where j=0,1....n and *count* is the iteration number and ε is sufficiently small positive real value.

variation 2:crisp coefficient parameters, fuzzy constant parameter

The variation 2 can be treated as a special case of variation 1 thus (F1) mildly generalizes (F2). In evaluating the parameters of model (F2) the constant parameter is treated as a crisp value, the resulting n+1 equations are solved for n+1 unknown parameters.

2.1.4 Solution of fuzzy least square problem : Crisp input and fuzzy output

variation 3: fuzzy coefficient parameters, fuzzy constant parameter

Solution of fuzzy least square problem with crisp input and fuzzy model parameters, comprises essentially the following steps

Step (i) : Preprocess or transform (scale) the data.

Step (ii) : Fuzzify the output (if necessary)

Step (iii) : Evaluate the classical function basing on d^2_{LR} metric

Step (iv) : Get the simultaneous equations by partially differentiating the classical function with respective to each parameter.

Step (v) : Solve the simultaneous equations to get the model parameter

Details of each of the step are as follows :

Step (i ii) : Evaluation of classical function

Suppose that data pairs $x_{i,j}$, $\tilde{Y}_i$ i=1,2,..m and j=1,2….n are observed, where the real numbers $x_{i,j}$ are non-negative and each $\tilde{Y}_i$ is fuzzy. The model can be defined by

$$\tilde{Y} = \tilde{A}_0 + \sum_{j=1}^{n} \tilde{A}_j X_j \ , \qquad \text{where } X_j \in R, \quad \tilde{A}_0, \tilde{A}_j \in F_T(R)$$

i.e.

$$\tilde{Y}_i = \tilde{A}_0 + \sum_{j=1}^{n} \tilde{A}_j x_{ij} \qquad .i = 1,2,\ldots\ldots m$$

is to be fitted to the data with respective to the best d_{LR}-fit.

Assuming $x_{i0} = 1.0$ for i=1,2…m one can write (1) as

$$\tilde{Y}_i = \sum_{j=0}^{n} \tilde{A}_j x_{ij} \qquad .i = 1,2,\ldots\ldots m$$

Considering distance as defined earlier the classical function to be minimized is evaluated as

(MR): minimize $r(A_j)$ is $d^2_{LR} = \sum_{i=1}^{m} d^2_{LR}\left[\sum_{j=0}^{n} \tilde{A}_j x_{ij}, \tilde{Y}_i\right]$

Assuming Y and A to be fuzzy LR numbers given by

$$\tilde{Y}_i = \left(y_{m_i}, y_{\alpha_i}, y_{\beta_i}\right) \qquad i = 1,2,\ldots..m$$

$$\tilde{A}_j = \left(a_{m_i}, a_{\alpha_i}, a_{\beta_i}\right) \qquad j = 0,1,2,\ldots n$$

Then the classical function can be expressed as

$$d_E^2 = \sum_{i=1}^{n}\left[\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_j}\right)^2 + \left(\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_j}\right) - \left(\sum_{j=0}^{n} a_{\alpha_j} x_{ij} - y_{\alpha_j}\right)\right)^2 + \left(\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_j}\right) - \left(\sum_{j=0}^{n} a_{\beta_j} x_{ij} - y_{\beta_j}\right)\right)\right]$$

........................(2.9)

Step (iv) : Partial Differentiation of Classical Function

The parameters a_j where j=0,…n can be determined by classical minimization of the real valued function. Partially differentiating the classical function with respective to each parameter of the model

Parameter a_{m_l} : $\dfrac{\partial d_{LR}}{\partial a_{m_l}} = 0$ $\quad l$=0,1,…n $\quad$ (I)

Parameter a_{α_l} : $\dfrac{\partial d_{LR}}{\partial a_{\alpha_l}} = 0$ $\quad l$=0,1,…n $\quad$ (II)

Parameter a_{β_l} : $\dfrac{\partial d_{LR}}{\partial a_{\beta_l}} = 0$ $\quad l$=0,1,…n $\quad$ (III)

By partial differentiation of the classical function and equating every equation to zero, the resulting algebraic system of $3n$+3 equations in the $3n$+3 unknowns are as follows

Eq. (I) results the following n+1 equations

$$\left\{\begin{array}{l} x_{il}\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_j}\right) + x_{il}\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_j} - \sum_{j=0}^{n} a_{\alpha_j} x_{ij} + y_{\alpha_i}\right) + \\ x_{il}\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_j} - \sum_{j=0}^{n} a_{\beta_j} x_{ij} + y_{\beta_i}\right) \end{array}\right\} = 0$$

where l = 0,1,2,…..n+1

Eq.(II) results the following n+1 equations

$$\sum_{i=1}^{m} x_{il}\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_i} - \sum_{j=0}^{n} a_{\alpha_j} x_{ij} + y_{\alpha_i}\right) = 0$$

where l = 0,1,2........n+1

Eq.(III) results the following n+1 equations

$$\sum_{i=1}^{m} x_{il}\left(\sum_{j=0}^{n} a_{m_j} x_{ij} - y_{m_i} - \sum_{j=0}^{n} a_{\beta_j} x_{ij} + y_{\beta_i}\right) = 0$$

where l = 0,1,2........n+1.

Step (v) Solution to the simultaneous equations

These equations are solved in a straightforward way using matrix inversion technique and the parameters of the model are obtained.

variation 4:crisp coefficient parameters, fuzzy constant parameter

The variation 4 is defined as follows

variation 4: $\tilde{Y} = \tilde{A}_0 + \sum_{j=1}^{n} a_j X_j$, where $X_j, a_j \in R$, $A_0 \in F_T(R)$

It can be clearly noticed that the variation 4 is a special case of variation 3 with crisp coefficient parameters of each input and fuzzy constant parameter. Thus applying the same procedure for variation 4 the n+3 unknown equations are obtained from the classical function and the n+1 parameters of the model are obtained by solving them using matrix inversion technique.

variation 5:crisp constant and coefficient parameters with crisp input

The variation 5 is defined as follows

variation 5: $Y = a_0 + \sum_{j=1}^{n} a_j X_j$, where $X_j, a_j, a_0 \in R$

Variation 5 is nothing but the conventional regression analysis. This is treated as a special case of fuzzy regression analysis for the convenience in generalizing the fuzzy regression analysis. The analysis of this variation is carried out in the conventional way.

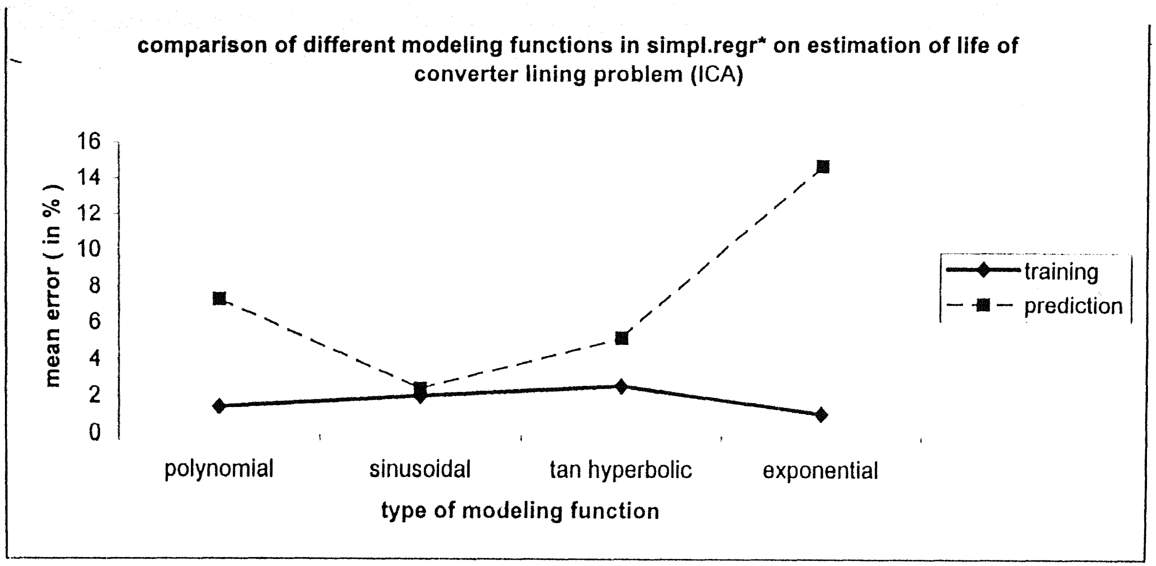

Fig 2.1: comparison of different modeling functions for simpl.regr using variation 5 on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
modeling functions	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	1.43	0.04	0.54	1.33	4.75	0.05	1	7.31	0.67	5.8	3.71	11.02	3.61	0.96
sinusoidal	2.02	0.09	0.82	2.17	6.56	0.04	1	2.4	0.06	1.77	0.73	3.13	1.67	0.98
tan hyperbolic	2.53	0.14	1.03	2.73	8.72	0.1	1	5.18	0.28	3.72	0.95	6.13	4.23	0.99
exponential	1.07	0.02	0.39	0.92	3.42	0.1	1	14.66	2.27	10.66	3.48	18.15	11.18	0.85

Table 2.1 : comparison of different modeling functions for simpl.regr using variation 5 on estimation of life of converter lining problem (ICA)

* simpl.regr means simple regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

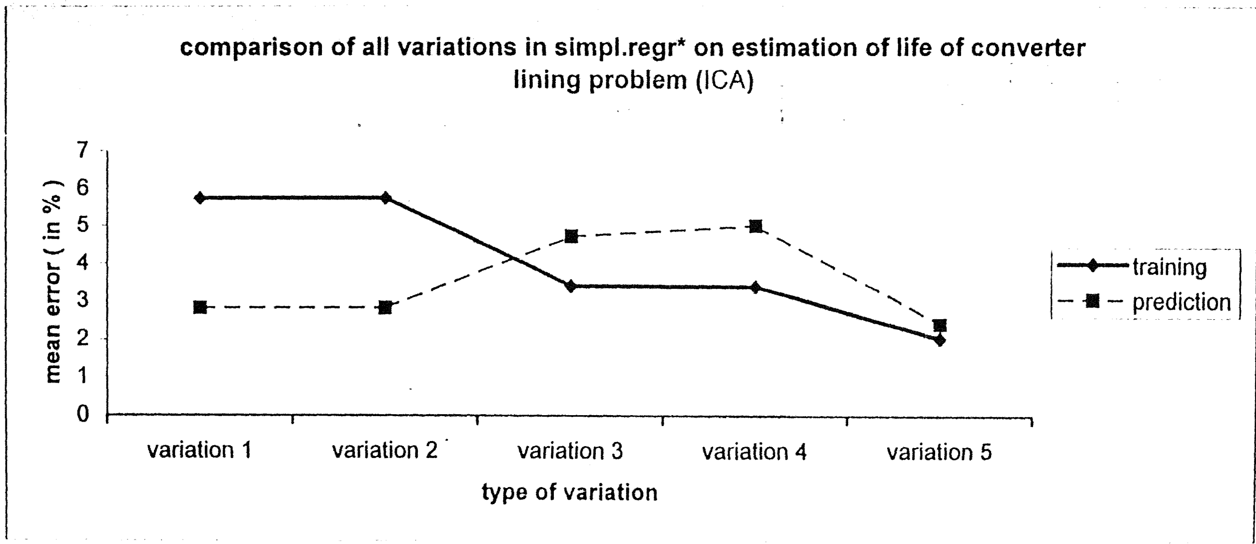

Fig 2.2 : Comparison of all variations for simpl.regr using sin modeling function on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
variation type	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	5.74	0.57	2.09	4.86	18.87	1.44	1.02	2.82	0.1	2.22	1.37	4.2	1.45	0.97
variation 2	5.74	0.57	2.09	4.86	18.87	1.44	1.02	2.82	0.1	2.22	1.37	4.2	1.45	0.97
variation 3	3.4	0.13	1	1.23	5.67	1.58	0.98	4.71	0.23	3.37	0.71	5.42	4	0.95
variation 4	3.38	0.13	1	1.25	5.38	1.52	0.98	4.99	0.26	3.59	0.96	5.94	4.03	0.95
variation 5	2.02	0.09	0.82	2.17	6.56	0.04	1	2.4	0.06	1.77	0.73	3.13	1.67	0.98

Table 2.2 : Comparison of all variations for simpl.regr using sin modeling function on estimation of life of converter lining problem (ICA)

* simpl.regr means simple regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

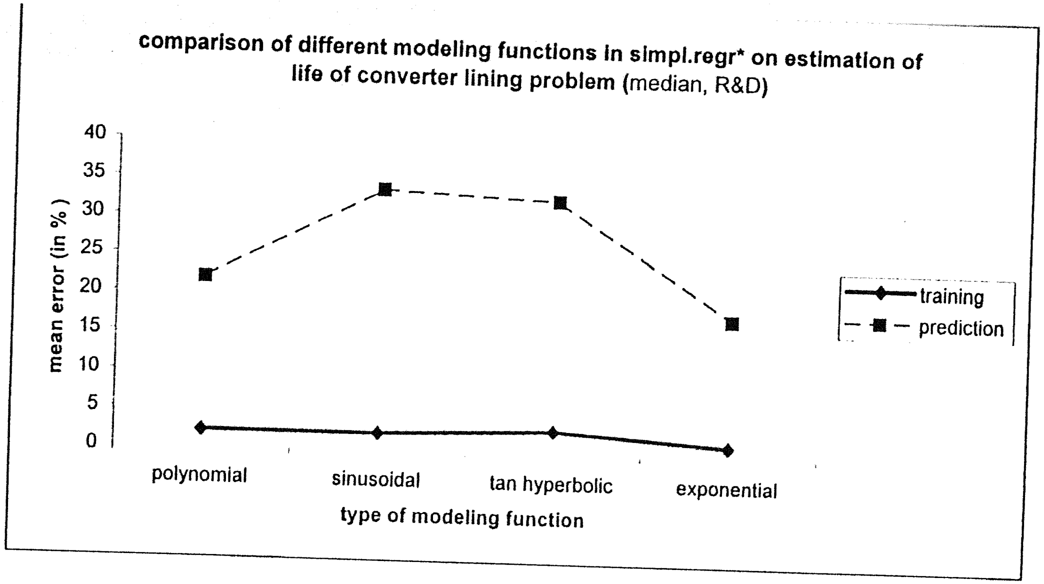

Fig 2.3 : comparison of different modeling functions in simpl.regr variation 5 on problem of estimation of life of converter lining (median R&D)

modeling function	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	2.2	0.07	0.75	1.58	6.17	0.14	1	21.99	6.97	18.67	14.61	36.6	7.38	1.22
sinusoidal	2.19	0.07	0.73	1.47	4.99	0.23	1	33.65	18.96	30.79	27.63	61.28	6.03	1.34
tan hyperbolic	2.88	0.13	1.01	2.19	6.53	0.02	1	32.56	20.38	31.92	31.28	63.84	1.28	1.31
exponential	1.35	0.02	0.44	0.81	2.78	0.24	1	17.55	4.82	15.52	13.18	30.73	4.36	0.87

Table 2.3 : comparison of different modeling functions in simpl.regr variation 5 on problem of estimation of life of converter lining (median R&D)

* simpl.regr means simple regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

2.1.5 Results and discussion

The models developed in the previous sections are applied to the problems of estimation of life of converter lining and modeling of Box Jenkins' gas furnace. For all the problems, the fuzzification constants are kept as follows

$\alpha_{in}= 0.9$ $\beta_{in} = 0.8$

$\alpha_{out}=1.0$ $\beta_{out}=1.3$

and the data is scaled between 0.0 and 1.0

2.1.5.1 Results for estimation of life of converter lining

i. Results for estimation of life of converter lining (ICA)

From the Table A it can be deduced that the variation 1 and variation 2 has large training error compared to variation 5 but a lower prediction error. For example the training error of the variation 2 using tan hyperbolic (*tanh*) modeling function, in TableA has a training error of 5.97 but the prediction error is 0.36 where as the variation 5 for the same modeling function has a training error of 2.53 but the prediction error is much higher as 5.18. In Table A for variation 4 using *exponential* modeling function the training error is 2.47 and the prediction error is 17.25. A typical comparison of modeling functions for variation 5 can be seen in the Fig 2.1 and Table 2.1 It can be seen that the *sin* and *tanh* give good results for all variations and the *exponential* modeling function shows a worst performance. Also comparison of all variations for *sin* modeling function can be seen in the Fig 2.2 and Table 2.2. It can be observed that for *sin* modeling function variation 5 shows better performance with the training error 2.02 and prediction error 2.4.

ii. Results for estimation of life of converter lining (median, R&D)

The results of the problem are given in Table B. From these results it can be observed that the trend followed in this problem is same as in the case of (ICA) problem but the effect of the modeling function has changed in this case. For the variations 1 and 2 the *sin* and *tanh* modeling functions give good results, but for variations 3, 4 and 5 they give poor results. For example, the variation 1 using *sin* modeling function has the training error 7.61 and prediction error 16.78 where as for variation 5 using *sin* modeling function the training error is 2.19 and the prediction error is 33.65. For variation 3, 4 and 5 *exponential* modeling function is giving good results in the prediction. A comparison of modeling functions for variation 5 is given in the Table 2.3 and Fig 2.3 from the graph it can be observed that the effect of modeling functions on the training is low for all the variations. Also the comparison of all variations for *exponential* modeling function can be observed

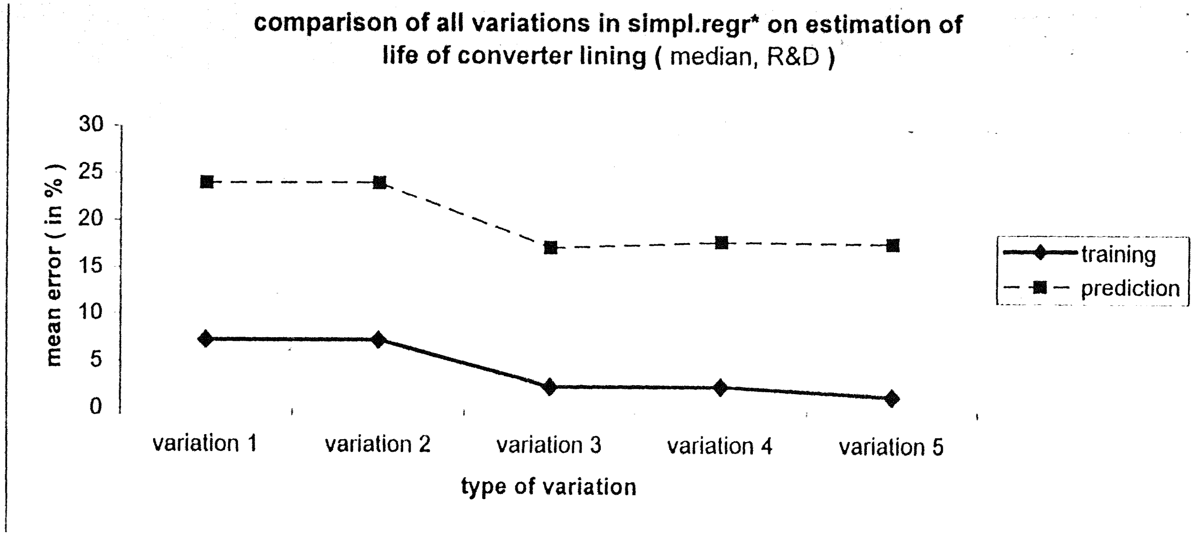

Fig 2.4 : comparison of all variations in simpl.regr using exponential modeling function on problem of estimation of life of converter lining (median R&D)

	training statistics								prediction statistics						
variation type	mn.error	ms error	rms error	error std	max error	min error	slope		mn error	ms error	rms error	error std	max error	min error	slope
variation 1	7.29	0.95	2.7	6.48	20.61	0.51	1.02		23.98	7.37	19.2	12.73	36.71	11.25	0.76
variation 2	7.29	0.95	2.7	6.48	20.61	0.51	1.02		23.98	7.37	19.2	12.73	36.71	11.25	0.76
variation 3	2.38	0.08	0.77	1.45	4.6	0.17	0.98		17.13	5.26	16.21	15.24	32.37	1.89	0.85
variation 4	2.41	0.08	0.79	1.53	4.61	0.04	0.98		17.78	5.65	16.8	15.77	33.55	2.01	0.84
variation 5	1.35	0.02	0.44	0.81	2.78	0.24	1		17.55	4.82	15.52	13.18	30.73	4.36	0.87

Table 2.4 : comparison of all variations in simpl regr. using exponential modeling function on problem of estimation of life of converter lining (median R&D)

* simpl.regr means simple regression model

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

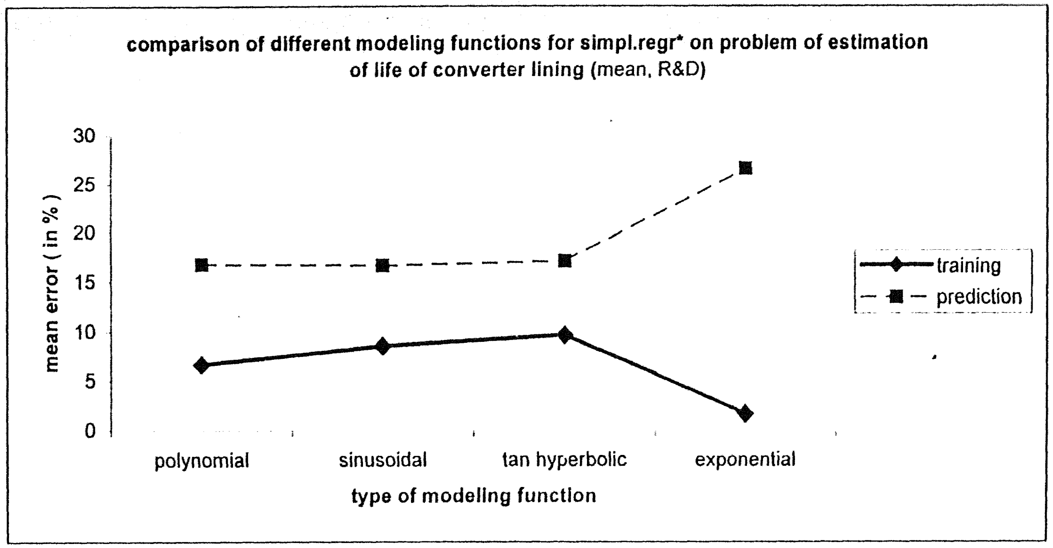

Fig 2.5 : comparison of different modeling functions in simpl.regr using variation 1 on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
modeling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	6.65	0.73	2.36	5.34	18.7	0.45	1.02	16.79	3.33	12.91	7.18	23.97	9.61	1.17
sinusoidal	8.55	1.13	2.95	6.33	19.31	1.44	1.03	16.68	2.99	12.23	4.54	21.22	12.15	1.17
tan hyperbolic	9.65	1.36	3.24	6.59	21.03	2.13	1.03	17.13	4.67	15.28	13.17	30.3	3.96	1.17
exponential	1.67	0.06	0.68	1.78	5.73	0.04	1.02	26.59	7.26	19.05	4.39	30.98	22.19	1.27

Table 2.5 : comparison of different modeling functions in simpl.regr using variation 1 on problem of estimation of life of converter lining (mean, R&D)

* simpl.regr means simple regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

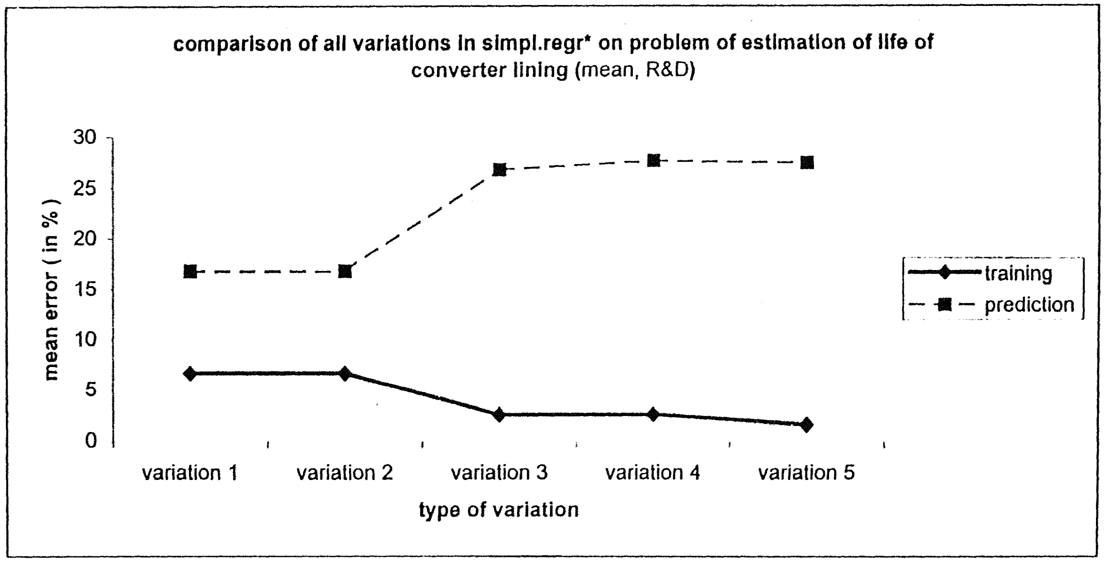

Fig 2.6 : comparision of all variations in simpl.regr using polynomial modeling function on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
variation type	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	6.65	0.73	2.36	5.34	18.7	0.45	1.02	16.79	3.33	12.91	7.18	23.97	9.61	1.17
variation 2	6.65	0.73	2.36	5.34	18.7	0.45	1.02	16.79	3.33	12.91	7.18	23.97	9.61	1.17
variation 3	2.54	0.1	0.86	1.78	6.93	0.32	0.98	26.77	8.92	21.12	13.24	40.01	13.53	1.13
variation 4	2.58	0.1	0.88	1.86	7.56	0.33	0.98	27.65	9.44	21.72	13.4	41.04	14.25	1.13
variation 5	1.6	0.04	0.58	1.35	4.67	0.07	1	27.42	10.07	22.44	15.99	43.4	11.43	1.16

Table 2.6 : comparision of all variations in simpl.regr using polynomial modeling function on problem of estimation of life of converter lining (mean, R&D)

* simpl.regr means simple regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

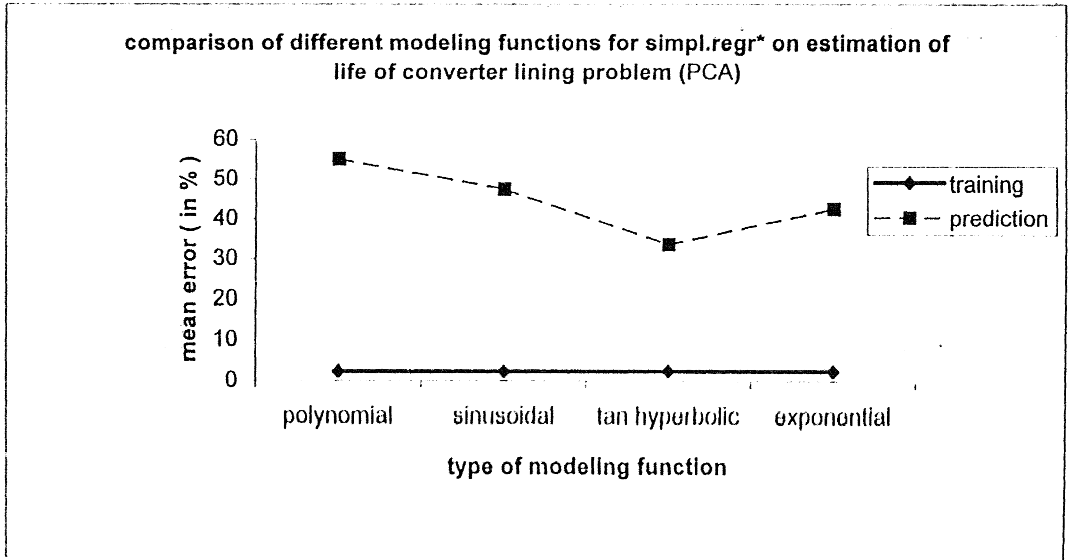

Fig 2.7 : Comparison of different modeling functions in simpl.regr variation 3 on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
modeling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	2.35	0.06	0.68	0.74	3.34	0.84	0.98	55.1	39.98	44.71	31.02	86.12	24.08	1.55
sinusoidal	2.38	0.07	0.72	1.06	3.76	0.36	0.98	47.46	23.51	34.28	9.9	57.36	37.56	1.47
tan hyperbolic	2.43	0.07	0.74	1.1	4.12	0.7	0.98	33.57	11.28	23.75	0.96	34.53	32.61	1.34
exponential	2.38	0.06	0.67	0.28	2.86	1.89	0.98	42.62	35.74	42.27	41.92	84.54	0.7	1.42

Table 2.7 : Comparison of different modeling functions in simpl.regr variation 3 on estimation of life of converter lining problem (PCA)

*simpl.regr means simple regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

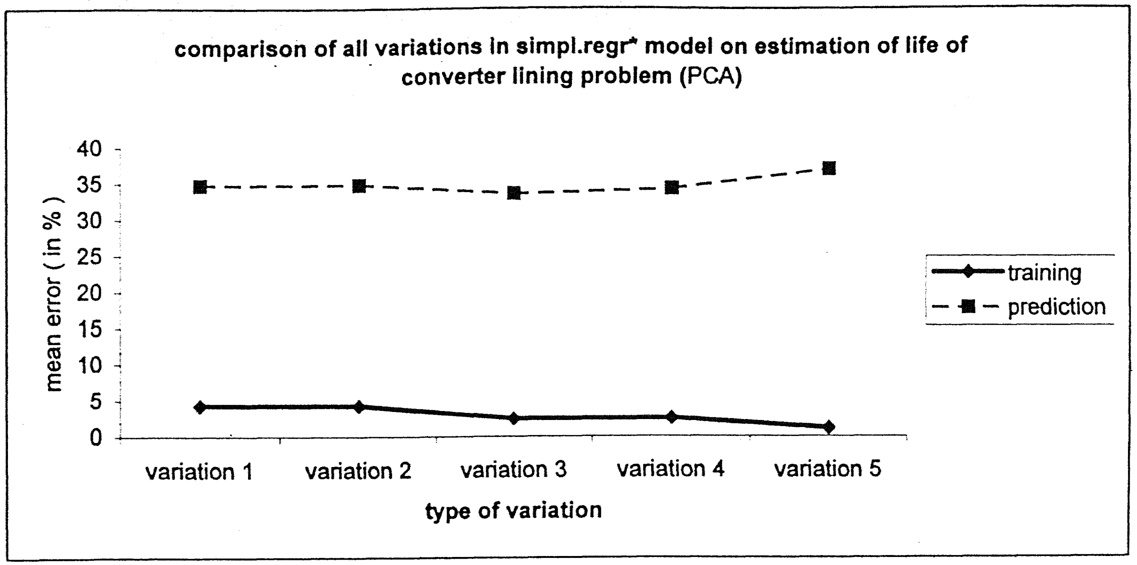

Fig 2.8 : comparison of all variations in simpl.regr using tanh modeling function on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
type of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max err	min err	slope
variation 1	4.23	0.31	1.55	3.64	12.32	0.62	1.02	34.81	12.6	25.1	6.94	41.75	27.87	1.35
variation 2	4.23	0.31	1.55	3.64	12.32	0.62	1.02	34.81	12.6	25.1	6.94	41.75	27.87	1.35
variation 3	2.43	0.07	0.74	1.1	4.12	0.7	0.98	33.57	11.28	23.75	0.96	34.53	32.61	1.34
variation 4	2.46	0.07	0.75	1.15	4.63	0.41	0.98	34.25	11.74	24.23	0.75	35.01	33.5	1.34
variation 5	1.08	0.02	0.37	0.8	3.17	0.1	1	36.85	13.59	26.07	0.98	37.84	35.87	1.37

Table 2.8 : comparison of all variations in simpl.regr using tanh modeling function on estimation of life of converter lining problem (PCA)

*simpl.regr means simple regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

2. Fuzzy opposite

$-M= -(m,\alpha,\beta)=(-m,\alpha,\beta)$ R-L numbers

3. Fuzzy subtraction

The subtraction has sense only between L-R and R-L, L-L and L-L,R-R and R-R numbers (not between R-L and R-L numbers)

$$M-N = M+(-N)$$

4. Fuzzy inverse

$1/m= (1/m,\beta/m^2,\alpha/m^2)$ R- number

5. Fuzzy multiplication

Three cases are distinguished:

Case A: If m>0 and n>0, then

$$MN=(m,\alpha,\beta)(n,\gamma,\delta)=(mn,n\alpha-m\delta,n\beta-m\gamma)= -[(-(m,\alpha,\beta))(n,\gamma,\delta)]$$

Case B: If m<0 and n>0, then

$$MN=(m,\alpha,\beta)(n,\gamma,\delta)=(mn,m\gamma+m\alpha,m\delta+m\beta)$$

Case C: If m<0 and n<0, then

$$MN=(m,\alpha,\beta)(n,\gamma,\delta)=(mn,-n\beta-m\delta,-n\alpha-m\gamma) = -[(-(m,\alpha,\beta))(-(n,\gamma,\delta))]$$

6. Fuzzy division

$$M/N=M.(1/N)=(m,\alpha,\beta)(n,\gamma,\delta)+(mn,(m\delta+n\alpha)/n^2,(m\gamma+n\beta)/n^2)$$

A.2 Method of Fuzzification

The method of fuzzification used in the present work is a simple method where the standard deviation of all the samples for each variable is used as the spread of the fuzzy number of that corresponding variable. The spread can be multiplied by any numeric constant in order to weigh the spread. The fuzzified number of any variable *x* is given as $\tilde{X} = (x,\alpha\sigma,\beta\sigma)$ where α and β are constants, σ is the standard deviation of *x* in observed samples.

A.3 Method of Defuzzification

the crisp value of a fuzzy number is evaluated by defuzzifying the corresponding fuzzy number with a suitable defuzzification technique. The present work applies the standard center of gravity method to defuzzify the fuzzy number.

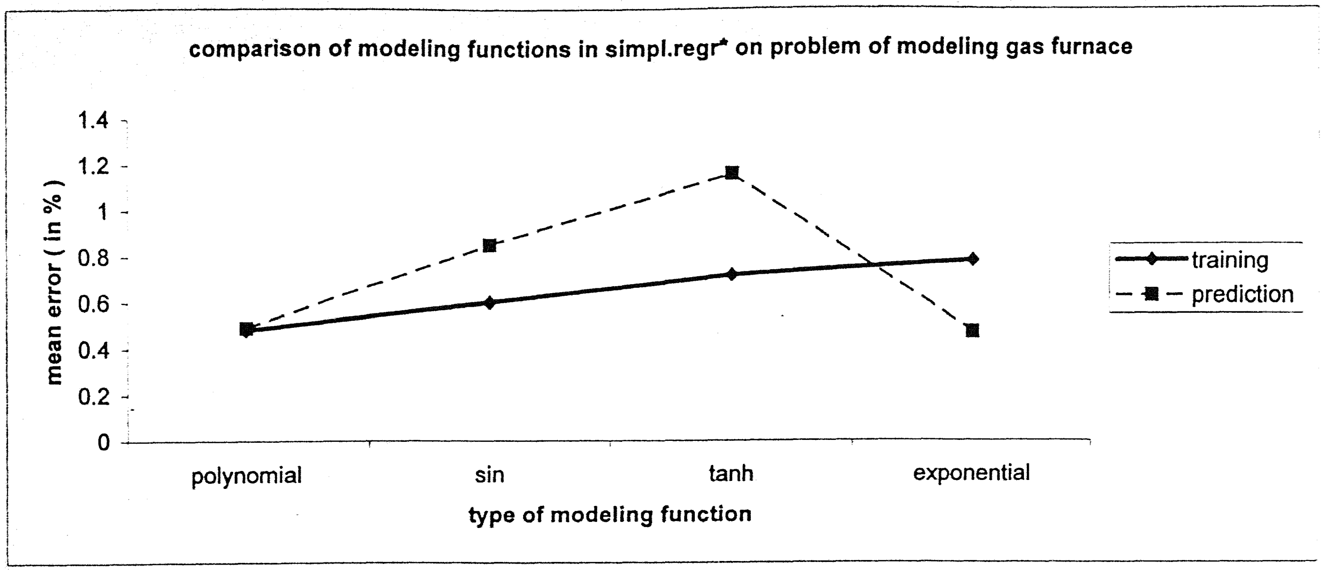

Fig 2.9 : comparison of all modeling functions in simpl.regr using variation 5 on problem of modeling of Box Jenkins' gas furnace

	training statistics							prediction statistics						
eling function	mn error	ms error	rms error	std error	max error	min error	slope	mn error	ms error	rms error	std error	max error	min error	slope
olynomial	0.48	0	0.04	0.47	3.87	0	1	0.49	0	0.41	0.32	0.8	0.17	1
sin	0.6	0.01	0.05	0.56	4.21	0	1	0.85	0.01	0.69	0.49	1.34	0.35	0.99
tanh	0.72	0.01	0.06	0.67	4.25	0	1	1.16	0.02	0.9	0.5	1.66	0.66	0.99
xponential	0.78	0.01	0.06	0.65	3.56	0	1	0.47	0	0.44	0.4	0.87	0.07	1

Table 2.9 : comparison of all modeling functions in simpl.regr using variation 5 on problem of modeling of Box Jenkins' gas furnace

* simpl.regr means simple regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

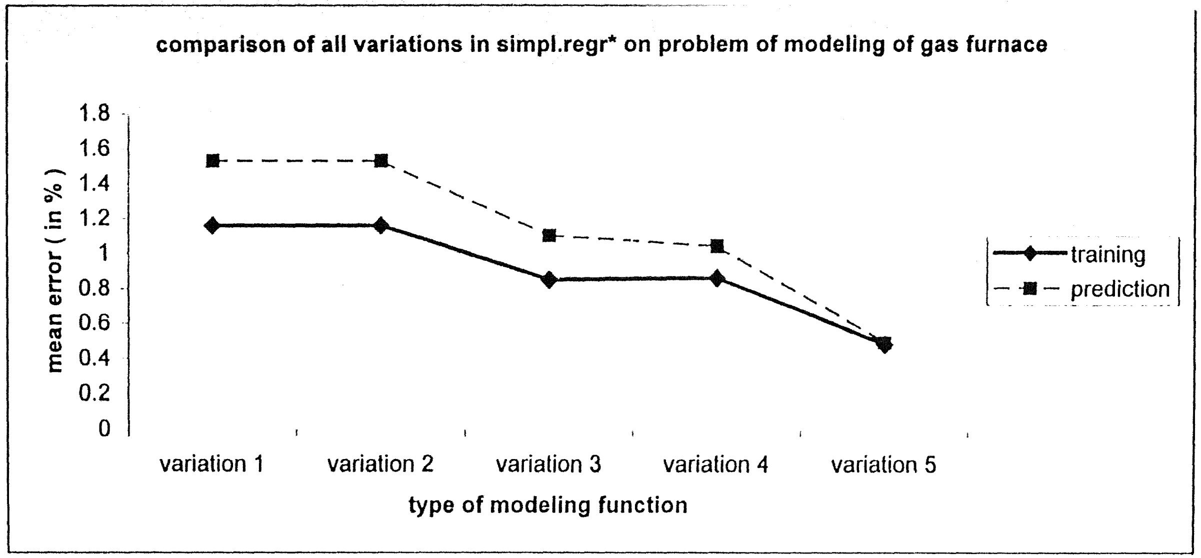

Fig 2.10 : comparison of all variations in simpl.regr using polynomial modeling functions on problem of modeling of Box Jenkins' gas furnace

	training statistics							prediction statistics						
pe of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	1.16	0.02	0.09	0.98	6.74	0	1.01	1.53	0.03	1.18	0.69	2.21	0.84	1.02
variation 2	1.16	0.02	0.09	0.98	6.74	0	1.01	1.53	0.03	1.18	0.69	2.21	0.84	1.02
variation 3	0.85	0.01	0.06	0.57	4.63	0	0.99	1.1	0.01	0.85	0.48	1.59	0.62	0.99
variation 4	0.86	0.01	0.06	0.57	4.72	0	0.99	1.04	0.01	0.81	0.48	1.52	0.56	0.99
variation 5	0.48	0	0.04	0.47	3.87	0	1	0.49	0	0.41	0.32	0.8	0.17	1

Table 2.10 : comparison of all variations in simpl.regr using polynomial modeling functions on problem of modeling of Box Jenkins' gas furnace

* simpl.regr means simple regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

in the Fig 2.4 and Table 2.4 that the variation 5 shows better performance for the *exponential* modeling function.

iii. Results for estimation of life of converter lining (mean, R&D)

The results are tabulated in Table C. From these tables it is observed that the trend of variation 1 and 2 having poorer training but better prediction is retained. Modeling functions have considerable effect on both training and prediction. A typical comparison of modeling functions for variation 1 can be seen in the Fig 2.5 and Table 2.5. From the graph it can be seen that *exponential* modeling function reduces the training error but the prediction error increases, i.e. the training error is 1.67 where as the prediction error is 26.59. A comparison of all variations for *polynomial* modeling function can be seen in the Fig2.6 and Table 2.6, From the graph it can be observed that the variation 1 shows better performance than the other variations. For variation 1 the training and prediction errors are 6.65 and 16.79 where as for variation 5 the training error is 1.6 and prediction error is 27.42.

iv. Results for estimation of life of converter lining (PCA)

The results are tabulated in Table D. From these tables, again it is observed that the trend of variation 1 having poorer training but better prediction is retained. Modeling functions have considerable effect on both training and prediction. A typical comparison of modeling functions for variation 3 can be seen in the Fig 2.7 and Table 2.7. From the graph it can be observed that *polynomial* modeling function reduces the training error but the prediction error increases, i.e. the training error is 2.35 where as the prediction error is 55.1, but for *tanh* modeling function the training error is 2.43 and prediction error is33.57. A comparison of all variations for *tanh* modeling function can be seen in the Fig 2.8 and Table 2.8, From the graph it can be observed that the variation 3 shows better performance than other variations. For variation 3 the training and prediction errors are 2.43 and 33.57 where as for variation 5 the training error is 1.08 and prediction error is 37.85.

2.1.5.2 Results for modeling of Box Jenkins' gas furnace problem

From the results tabulated in Table E one can observe that the conventional regression i.e. variation 5 yields good results when compared to other variations. The minimum training and prediction errors of the variation 5 are 0.48 and 0.48 respectively, but in variation 1 the training and prediction errors are 1.19 and 1.12 respectively. The effect of modeling function can be observed in the Fig.2.9 and Table 2.9. For this problem the simple polynomial modeling function gives better results. The effect of variation upon this problem can be seen in the Fig 2.10 and Table 2.10 for the *polynomial* modeling function.

2.1.6 Conclusions

In this present work, fuzzified least square regression modeling is developed. The effect of various modeling functions is studied for different variations of fuzzy regression models. Fuzzyfying the input leads to a poorer training but a better prediction, i.e. the variation 1 and 2 always shows a better prediction through the training is worse. The effect of modeling functions upon performance is totally dependent upon the input variables. The performance of each modeling function with every variation is almost constant. With box data the effect of modeling function is not considerable as the variation in data is very low.

2.2 A.R.M.A.

2.2.1 Introduction

Auto regressive moving average class of models [3] has become one of the most popular time series forecasting models. Quantitatively, especially to simulate and predict a time series one models it as the out put of the dynamic system whose input is white noise. Such a model can be described in several ways, but if *parsimonious parameterization* is required then ARMA model is employed. Suppose a time series Y(t), t = 0,±1,.. is considered . It is modeled as the out put of the system whose input is a white noise ε(t) and employing ARMA(p,q) with the representation as

$$Y(t)+\alpha(1)Y(t-1)+......+\alpha(p)Y(t-p)$$
$$= \varepsilon(t)+\beta(1)\varepsilon(t-1)+.......+\beta(q)\varepsilon(t-q)$$

or in operator notation

$$g(L)Y(t)=h(L)\varepsilon(t)$$

where

L is the lag (or backward shift) operator, LY(*t*) = Y(*t*-1)

$g(z) = 1+ \alpha(1)z+.............+\alpha(p)z^p$

$h(z) = 1+\beta(1)z+.............+\beta(q)z^q$

$\sigma^2 = E[|\varepsilon(i)|^2]$ is the variance of the white noise ε(t).

For this model to represent a stationary time series, the roots of the characteristic equation g(*z*) = 0 must lie outside the unit circle in the complex plane. An ARMA (p,q) model for a stationary time series has parameters

$$\alpha(1),......\alpha(p), \beta(1).........\beta(p), \sigma^2$$

and recursive least squares method is applied to estimate these parameters.

The present work extends the ARMA model to the identification of a multi input single output system as suggested in [12]. It presents a way to fuzzify the developed ARMA models using all the variations developed in the fuzzy regression analysis. A comparison of performance for conventional and fuzzified ARMA is provided. with two example problems, estimation of life of converter lining and modeling of Box Jenkins' gas furnace.

2.2.2 Formulation of fuzzy ARMA

Formulation of fuzzy ARMA comprises essentially the following steps

Step (i) : Preprocess or Scale the data (as described previously)

Step (ii) : Formulate [Y(N)], [ϕ (N)] and [θ] from the observed (available) data

Step (iii): Fuzzify [Y(N)] and [ϕ(N)] (if necessary) (as described previously)

Step (iv) : Evaluate the model parameters by fuzzy least square regression modeling

Details of each step is given below:

Step (ii) Formulation of [Y(N)], [ϕ(N)] and [θ]

Let Y is the output vector of m number of samples and X_j ,j = 1,...n is the vector of m samples of j^{th} input variable, n is the number of input variables. Extending the concept of stationary time series modeling to multi input single output system as suggested by [12], a simple ARMA (p,q) model is considered for the system described above. Assuming p=q, the model can be written as

$$y(k)+\sum_{i=1}^{p} a_i y(k-i)=\sum_{i=1}^{p}\sum_{j=1}^{n} b_{ij}x_j(k-i) \qquad k = p,p+1,........m.$$

p is the order of the model.

a_i, b_{ij} are parameters describing the system.

Let $\theta=[a_1,a_2,....a_m,b_{11},b_{12},..b_{1n},b_{21},...b_{mn}]^T$

and $\phi(k)=[-y(k-1),-y(k-2),....x_1(k-1),........x_n(k-m)]^T$ k=m,m+1,.....N

$$\Phi(N)=[\phi(n),.................\phi(N)]^T$$

$$Y(N)=[y(n),................y(N)]^T$$

Step (iv) Evaluation of model parameters

Formulating the ARMA in the same method as the fuzzy regression analysis, the data is fitted in the sense of best fit with respective to the metric as described in section 2.1. where the corresponding least square model is represented as

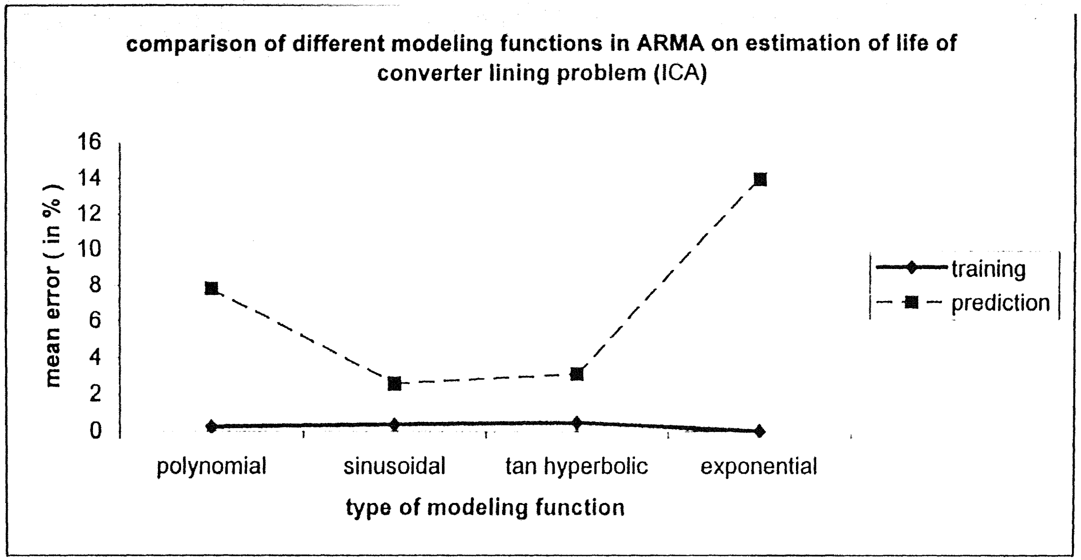

Fig 2.11 : comparison of different modeling functions in ARMA using variation 5 on estimation of life of converter lining problem (ICA)

	training statistics							prediction error						
modeling function	**mn error**	**ms error**	**rms error**	**error std**	**max error**	**min error**	**slope**	**mn error**	**ms error**	**rms error**	**error std**	**max error**	**min error**	**slope**
polynomial	0.26	0	0.09	0.15	0.65	0.04	1	7.81	0.69	5.86	2.77	10.58	5.04	1.08
sinusoidal	0.39	0	0.13	0.24	1.02	0.02	1	2.58	0.1	2.27	1.91	4.5	0.67	1.02
tan hyperbolic	0.47	0	0.16	0.3	1.28	0.13	1	3.09	0.12	2.47	1.63	4.72	1.46	0.98
exponential	0.04	0	0.01	0.02	0.08	0	1	13.93	2.06	10.14	3.41	17.34	10.52	1.14

Table 2.11 : comparison of different modeling functions in ARMA using variation 5 on estimation of life of converter lining problem (ICA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

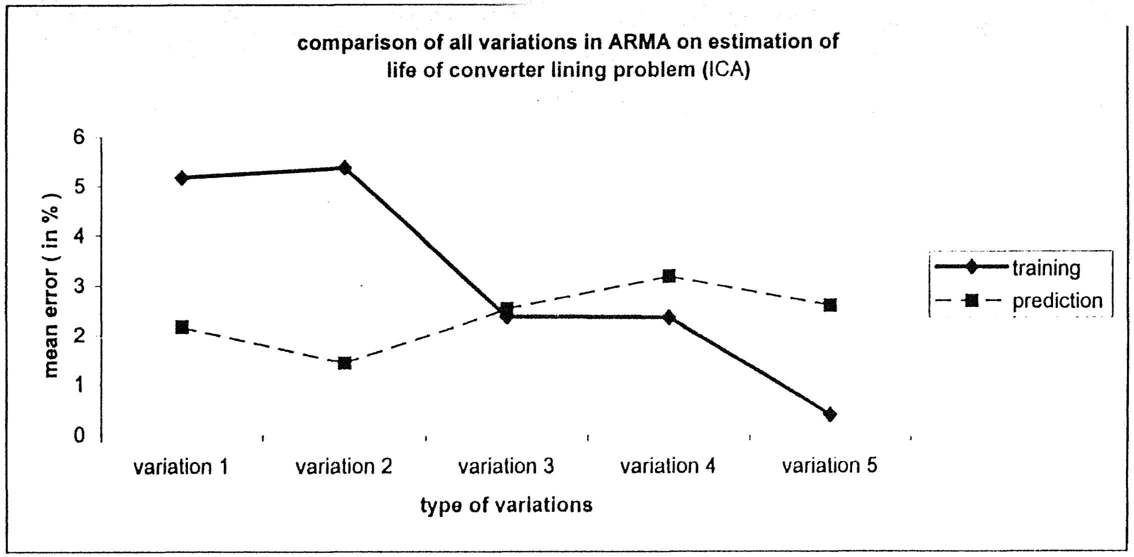

Fig 2.12 : comparison of all variations in ARMA using sin modeling function on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
variation type	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	5.17	0.34	1.68	2.7	9.82	1.08	0.98	2.17	0.06	1.76	1.22	3.4	0.95	0.98
variation 2	5.37	0.41	1.84	3.42	13.15	1.41	1.02	1.43	0.03	1.19	0.9	2.33	0.53	1.01
variation 3	2.37	0.06	0.7	0.45	2.95	1.38	0.98	2.52	0.07	1.82	0.5	3.02	2.02	0.99
variation 4	2.35	0.06	0.7	0.56	3.3	1.46	0.98	3.18	0.1	2.29	0.59	3.77	2.59	0.99
variation 5	0.39	0	0.13	0.24	1.02	0.02	1	2.58	0.1	2.27	1.91	4.5	0.67	1.02

Table 2.12: comparison of all variations in ARMA using sin modeling function on estimation of life of converter lining problem (ICA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the element corresponding to the best performance

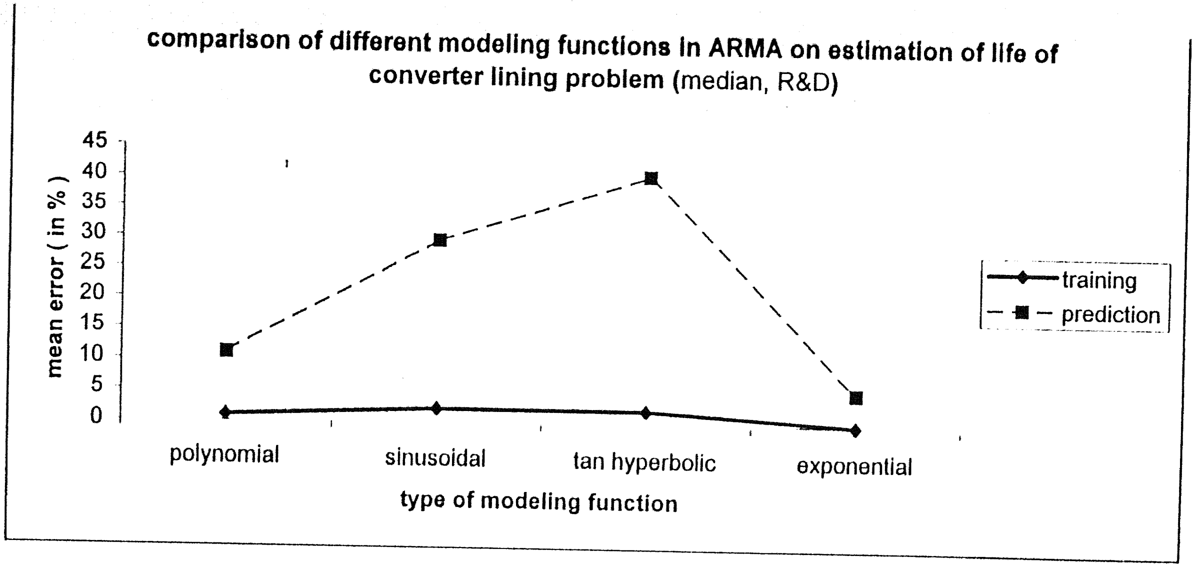

Fig 2.13 : comparison of different modeling functions used in ARMA varitiation 5 on estimation of life of converter lining problem (median R&D)

	training statistics							prediction statistics						
type of function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	1.04	0.02	0.36	0.7	2.25	0.07	1	11.06	1.25	7.91	1.65	12.71	9.41	1.02
sinusoidal	2.31	0.08	0.82	1.66	6.19	0	1	29.61	10.62	23.04	13.6	43.22	16.01	1.14
tan hyperbolic	2.24	0.09	0.84	1.88	7.03	0.19	1	40.44	29.05	38.11	35.64	76.08	4.8	1.36
exponential	0.1	0	0.03	0.07	0.24	0.02	1	5.22	0.39	4.43	3.47	8.88	1.75	1.03

Table 2.13 : comparison of different modeling functions used in ARMA varitiation 5 on estimation of life of converter lining problem (median R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

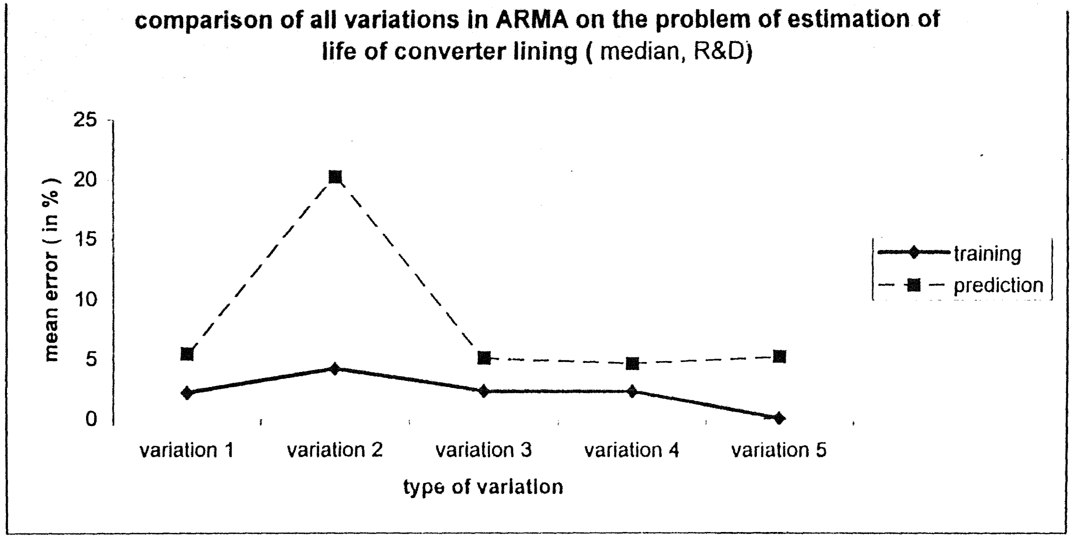

Fig 2.14 : comparison of all variations in ARMA using exponential modeling function on estimation of life of converter lining problem (median R&D)

	training statistics							prediction statistics						
type of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	2.2	0.06	0.71	1.12	3.75	0.36	0.98	5.47	0.3	3.87	0.28	5.74	5.19	1
variation 2	4.2	0.27	1.5	3.03	11.15	0.3	1.03	20.24	4.26	14.59	3.97	24.21	16.27	1.2
variation 3	2.36	0.06	0.68	0.12	2.6	2.15	0.98	5.09	0.27	3.67	1.01	6.11	4.08	1.01
variation 4	2.35	0.06	0.7	0.55	3.47	1.26	0.98	4.62	0.22	3.34	0.96	5.58	3.65	1.01
variation 5	0.1	0	0.03	0.07	0.24	0.02	1	5.22	0.39	4.43	3.47	8.68	1.75	1.03

Table 2.14 : comparison of all variations in ARMA using exponential modeling function on estimation of life of converter lining problem (median R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error

shaded row represents the best performance

$$Y(k) = \sum_{j=1}^{p(n+1)} \theta_j \phi_j(k) \qquad k = n,......m.$$

Models with all the variations and different modeling functions are developed.

2.2.3 Results and discussion

The models developed in ARMA are applied to the problems of estimation of life of converter lining and modeling of Box Jenkins' gas furnace. For all the problems, the fuzzification constants are kept as follows

$\alpha_{in} = 0.9 \qquad \beta_{in} = 0.8$

$\alpha_{out} = 1.0 \qquad \beta_{out} = 1.3$

the data is scaled between 0.0 and 1.0 and the optimum order of the model is found to be l

2.2.3.1 Results of estimation of life of converter lining problem

i. Results of estimation of life of converter lining problem (ICA)

From the results given in Table A, one can observe that the variation 5 with *sin* modeling function is giving better results, training error is 0.39 prediction error is 2.58. But variation 2 gives a better prediction with prediction error 1.43 though the training error is 5.37. For all variations the *exponential* modeling function gives the best training but a poor prediction, for example variation 5 has 0.04 training error but the prediction error is 13.93. This can be observed in the Fig 2.11 and Table 2.11 where a comparison of all modeling functions is brought out. From Fig 2.12 and Table 2.12 a comparison of all the variation can be observed for *sin* modeling function. Variation 5 gives better training and prediction results, with training error 0.39 and prediction error 2.58.

ii. Results of estimation of life of converter lining problem (median, R&D)

From the results given in Table B, it can be observed that the variation 5 with *exponential* modeling function is giving better results, training error is 0.1 prediction error is 5.22. But variation 4 gives a better prediction with prediction error 4.63 though the training error is 2.37. For all variations the *tanh* modeling function is giving the poor training and prediction, for example variation 5 has 2.24 training error and the prediction error is 40.44. This can be observed in the Fig 2.13 and Table 2.13 where a comparison of all the modeling function is shown that the *exponential* and *polynomial* modeling functions shows good performance. From Fig 2.14 and Table 2.14 a comparison of all the variation can be observed.

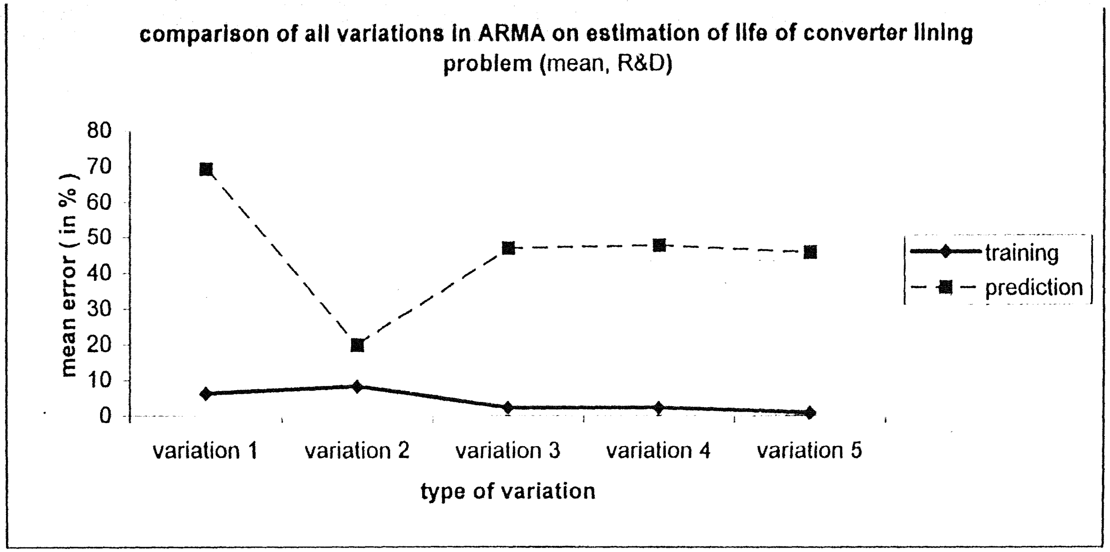

Fig 2.15 : comparison of in variations in ARMA with sin modeling function on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
variation type	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	6.14	0.58	2.2	4.49	15.38	0.01	0.97	69.3	56.26	53.04	28.71	98.01	40.59	1.69
variation 2	8.24	1.06	2.98	6.21	20.06	0.3	1.01	19.93	4.51	15.02	7.35	27.28	12.58	0.93
variation 3	2.37	0.07	0.75	1.08	4.51	0.86	0.98	46.91	26.71	36.54	21.67	68.58	25.24	0.53
variation 4	2.35	0.07	0.75	1.09	4.59	0.22	0.98	47.64	27.69	37.21	22.36	70	25.28	0.52
variation 5	0.95	0.01	0.32	0.58	2.19	0.22	1	45.63	25.74	35.88	22.2	67.82	23.43	0.54

Table 2.15 : comparison of all variations in ARMA with sin modeling function on problem of estimation of life of converter lining (mean, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

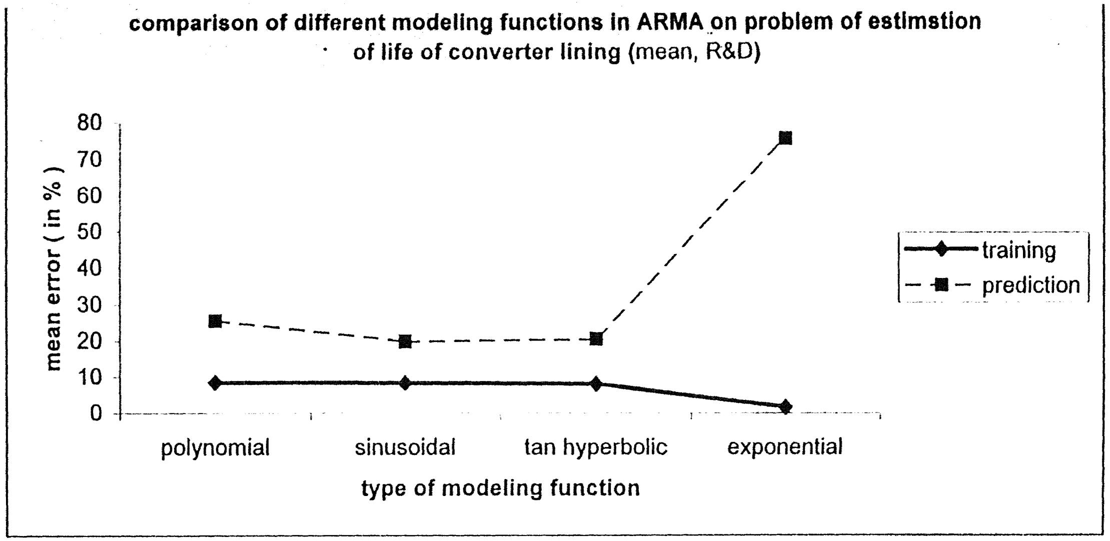

Figure 2.16 : comparison of different modeling functions in ARMA variation 2 on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
modeling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	8.46	1.08	2.99	6	21.15	2.69	1.01	25.59	11.33	23.8	21.86	47.45	3.73	0.74
sinusoidal	8.24	1.06	2.98	6.21	20.06	0.3	1.01	19.93	4.51	15.02	7.35	27.28	12.58	0.93
tan hyperbolic	8.04	0.97	2.85	5.72	20.1	0.51	1.01	20.56	4.64	15.23	6.4	26.96	14.17	1.06
exponential	1.65	0.04	0.59	1.22	3.83	0.22	1.02	75.48	57.64	53.69	8.23	83.71	67.24	0.25

Table 2.16 : comparison of different modeling functions in ARMA variation 2 on problem of estimation of life of converter lining (mean, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

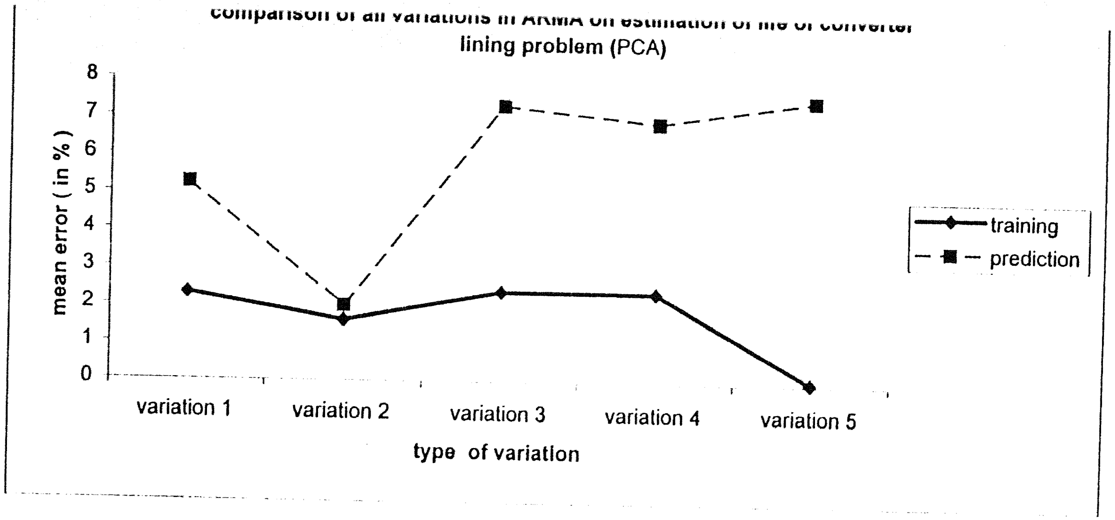

Fig 2.17 : comparison of all variations in ARMA using exponential modeling function on estimation of life of converter lining problem (PCA)

variation type	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max errror	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	2.31	0.06	0.69	0.63	3.52	1.11	0.98	5.25	0.38	4.39	3.3	8.55	1.95	0.95
variation 2	1.6	0.03	0.5	0.61	2.41	0.8	1.02	2	0.04	1.42	0.12	2.12	1.89	1
variation 3	2.39	0.06	0.69	0.05	2.46	2.29	0.98	7.3	0.53	5.16	0.07	7.37	7.23	1
variation 4	2.37	0.06	0.7	0.54	3.56	1.27	0.98	6.87	0.47	4.86	0.15	7.02	6.72	1
variation 5	0.05	0	0.02	0.03	0.11	0.01	1	7.48	0.62	5.55	2.38	9.86	5.1	1.02

Table 2.17 : comparison of all variations in ARMA using exponential modeling function on estimation of life of converter lining problem (PCA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the element corresponding to the best performance

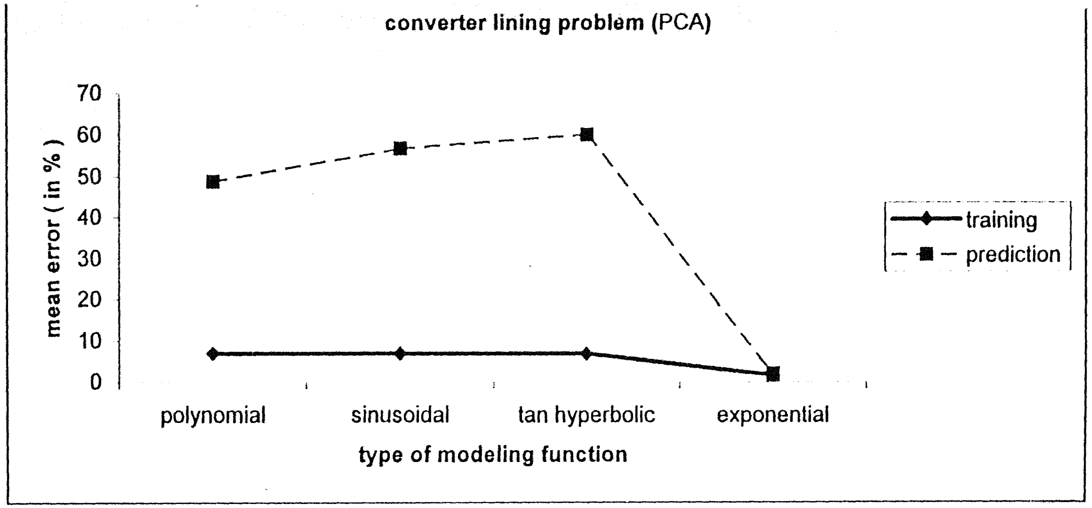

Fig 2.18: comparison of different modeling functions in ARMA variation 2 on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
modeling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	6.95	0.92	2.77	6.63	24.02	0.25	1.01	48.72	33.86	41.15	31.83	80.55	16.89	1.32
sinusoidal	6.82	0.85	2.66	6.18	22.63	0.24	1.01	56.72	53.65	51.79	46.34	103.06	10.38	1.46
tan hyperbolic	6.76	0.82	2.62	6.05	21.86	0.89	1.01	59.95	65.06	57.03	53.96	113.91	5.99	1.54
exponential	1.6	0.03	0.5	0.61	2.41	0.8	1.02	2	0.04	1.42	0.12	2.12	1.89	1

Table 2.18 : comparison of different modeling functions in ARMA variation 2 on estimation of life of converter lining problem (PCA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the element corresponding to the best performance

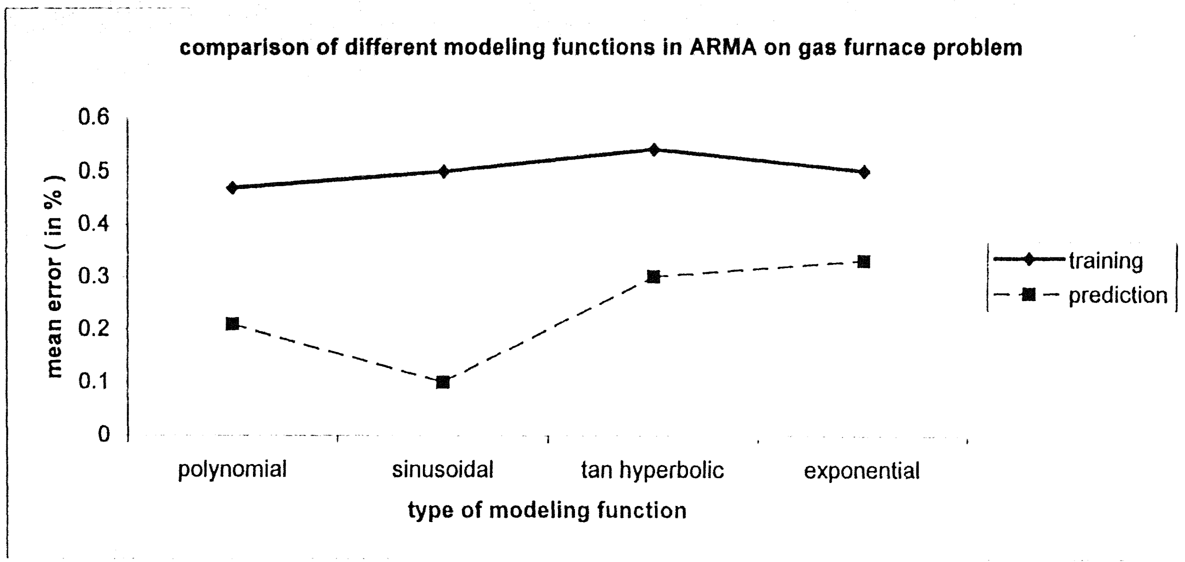

Fig 2.19 : comparison of different modeling functions in ARMA using variation 5 on modeling of Box Jenkins' gas furnace problem

	training statistics							prediction statistics						
modeling functions	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	0.47	0	0.04	0.45	3.84	0	1	0.21	0	0.18	0.16	0.36	0.05	1
sinusoidal	0.5	0	0.04	0.48	4.11	0	1	0.1	0	0.09	0.07	0.18	0.03	1
tan hyperbolic	0.54	0.01	0.04	0.5	4.11	0	1	0.3	0	0.21	0.02	0.32	0.28	1
exponential	0.5	0	0.04	0.44	2.73	0	1	0.33	0	0.28	0.21	0.54	0.12	1

Table 2.19 : comparison of different modeling functions in ARMA using variation 5 on modeling of Box Jenkins' gas furnace problem

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

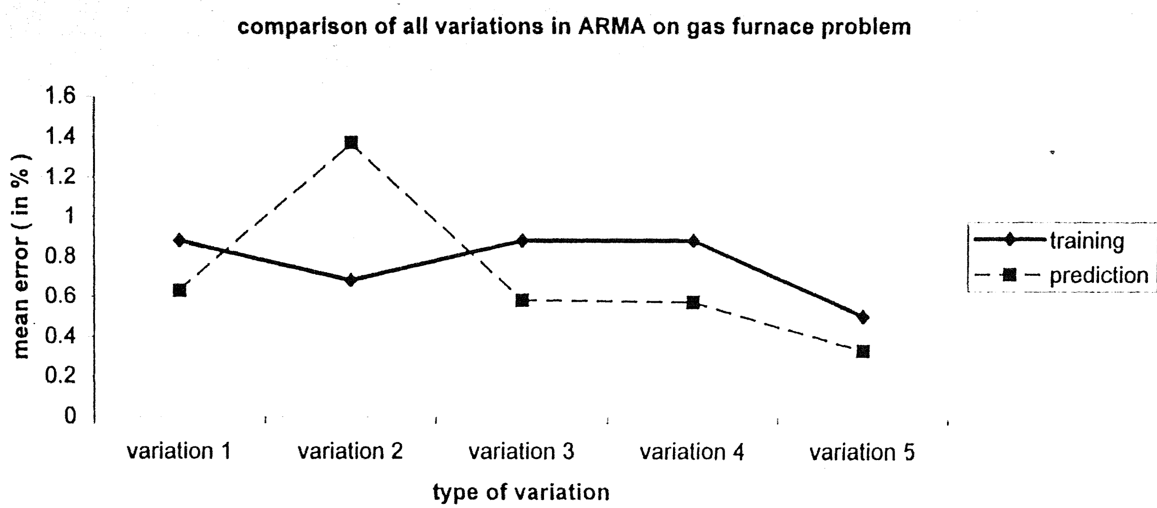

Fig 2.20: comparison of all variations in ARMA using exponential modeling function on modeling of Box Jenkins' gas furnace problem

	training statistics							prediction statistics						
type of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min eror	slope
variation 1	0.88	0.01	0.06	0.54	3.31	0.01	0.99	0.63	0	0.5	0.31	0.94	0.32	0.99
variation 2	0.68	0.01	0.05	0.55	3.42	0.01	1	1.37	0.02	1	0.34	1.71	1.04	1.01
variation 3	0.88	0.01	0.06	0.53	3.32	0	0.99	0.58	0	0.47	0.33	0.91	0.25	0.99
variation 4	0.88	0.01	0.06	0.53	3.32	0.01	0.99	0.57	0	0.47	0.33	0.9	0.24	0.99
variation 5	0.6	0	0.04	0.44	2.73	0	1	0.33	0	0.28	0.21	0.54	0.12	1

Table 2.20: comparison of all variations in ARMA using exponential modeling function on modeling of Box Jenkins' gas furnace problem

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

sults of estimation of life of converter lining problem (mean, R&D)

The results obtained are given in the Table C. From the results it can be deduced e variation 2 with *sin* modeling function gives good results, the training error is nd prediction error is 19.93. In this problem the variation 5 has better training but rediction, i.e. the training error is 0.95 where as prediction error is 45.0. This can be ved from the Fig 2.15 and Table 2.15. where a comparison is brought out for all var- s with *sin* modeling function. A typical comparison of the performance of all model- inction is shown in the Fig 2.16 and Table 2.16. It can be observed from the graph e *sin* and *tanh* modeling functions show better performance.

sults of estimation of life of converter lining problem (PCA)

The results obtained are given in the Table D. From the results it can be deduced ariation 2 with *exponential* modeling function gives good results, the training error and prediction error is 2.0. In this problem the variation 5 has got better training but prediction, i.e. the training error is 0.05 where as prediction error is 7.48. This can be ved from the Fig 2.17 and Table 2.17, where a comparison is brought out for all var- s with *exponential* modeling function. A typical comparison of the performance of odeling function is shown in the Fig 2.18 and Table 2.18 where one can observe that *nential* modeling function shows better performance with 1.6 training error and 2.0 ction error.

.2 Results of modeling of Box Jenkins' gas furnace

From the results given in Table E. it can be observed that the variation 5 with *sin* ling function is giving better results, training error is 0.45 prediction error is 0.1. For riations the *tanh* and *exponential* modeling functions are giving the poor training as as prediction, variation 5 has 0.54 training error and the prediction error is 0.33. This e observed in the Fig 2.19and Table 2.19 where a comparison of all the modeling fu- n is shown that the *sin* and *polynomial* modeling functions shows good performance. 1 Fig 2.20 and Table 2.20 a comparison of all the variation can be observed. Variation ows a good performance when compared to rest of the variations.

Conclusions

In this present work, fuzzified ARMA is developed by applying the fuzzy least res to the conventional ARMA technique. The effect of various modeling functions is ed for different variations of fuzzy ARMA models. From the results discussed above n be concluded that fuzzyfying the input leads to a poorer training but a better predic-

on, i.e. the variation 1 and 2 always shows a better prediction through the training is ʼorse. The performance of each modeling function with every variation is almost onstant. With Box data the effect of modeling function is not considerable as the variat-on in data is very low.

.3 Cluster Wise Regression

.3.1 Introduction

Regression analysis is generally used in the model-fitting of observations. The het-rogeneous problem in the regression model is usually difficult to be handled. The hetero-eneity of observed samples is because of different clusters of observations. In the present ork, the observed samples of the system are divided into optimum number of clusters ıen a separate model is developed for each cluster of observed samples. This facilitates ıe handling of heterogeneity in the data. All the variations of fuzzy least square regress-on developed in the chapter 2 are used for developing the models for each cluster. Comp-rison of performance of different clustering methods for different variations is presented ith two problems, estimation of life of converter lining and modeling Box Jenkins' gas urnace model.

.3.2 Formulation of cluster wise regression modeling

Formulation of cluster wise regression modeling comprises of the following steps.

tep (i) : Preprocess or Transform (scale) the data (as described previously)

tep (ii) : Classify the data based on the independent variables

tep (iii) : Fuzzify the data (as described previously, if necessary)

tep (iv) : Estimate the parameters of each model through fuzzy least square regression Modeling.

tep (ii) Classification of Data

Let ς be the set of observed (X_i, Y_i), $i = 1,\ldots\ldots,m$. Suppose these observations re heterogeneous and from different clusters of observations. The samples of observation re divided into c clusters considering each input as a feature. For clustering the data, met-ıods of clustering are employed.

1. Fuzzy c-means clustering
2. k-means clustering
3. self organizing map (SOM) clustering
4. Adaptive Resonance Theory 2 (ART 2) clustering

5.fuzzy Adaptive Resonance Theory (fuzzy ART) clustering.

Step (iv) Estimation of Model Parameters

The data set of each cluster is fitted in the sense of best fit with respective to the metric d_{LR} (as described in chapter 2), then the corresponding fuzzy least squares model to the model is represented as

$$Y_i^k = a_0^k + \sum_{j=1}^{n} a_j^k x_{i,j}^k \qquad i=1,2,....m \text{ and } k=1,2,......c$$

where a^k_0 and a^k_j are the unknown fuzzy parameters describing the model and $x^k_{i,j}$ is the j^{th} input of i^{th} sample belonging to k^{th} cluster. Different models are developed with all the variations and different modeling functions as derived in section 2.1.

2.3.3 Results and discussion

The developed models for clustering regression are applied for the estimation of life of converter lining problem. In all the problems the input data is sealed between 0 to 1. For the SOM the neighborhood size is varied between 0 to (number of clusters -1), the period is kept as 5 and the maximum limit of iterations is kept as 75. The factor α is kept 0.15. For ART2 the vigilance factor is varied between 0.9 to 4.6 and optimum value is found to be 3.2.For fuzzy ART2 the vigilance factor is varied between 0.5 to 0.99 and the optimum value is found as 0.76 . The factor α. and β are kept as 0.18 and 0.5 as per the specification in [14].

2.3.3.1 Results of estimation of life of converter lining problem

i. Results of estimation of life of converter lining problem (ICA)

From the results given in Table A, one can observe that the training error reduces as the number of cluster increases but the prediction has no consistency with the number of clusters. In different methods of clustering, for different variations it has different behavior with the increase of number of clusters. For example, with fuzzy c-mean clustering in the variation1, the better performance is with five clusters i.e. the training error is 1.58 and prediction error is 5.70. In variation 4, it is with two clusters, the training error is 2.43 and the prediction error is 2.97. Also it can be seen that with the SOM clustering method the variation 4 using *exponential* modeling function has the best performance having a training error of 2.4 and prediction error of 0.29.

A comparison of performance of modeling function can be studied from the Table 2.23 and Fig 2.23 or the variation 5 with three clusters using SOM clustering method.

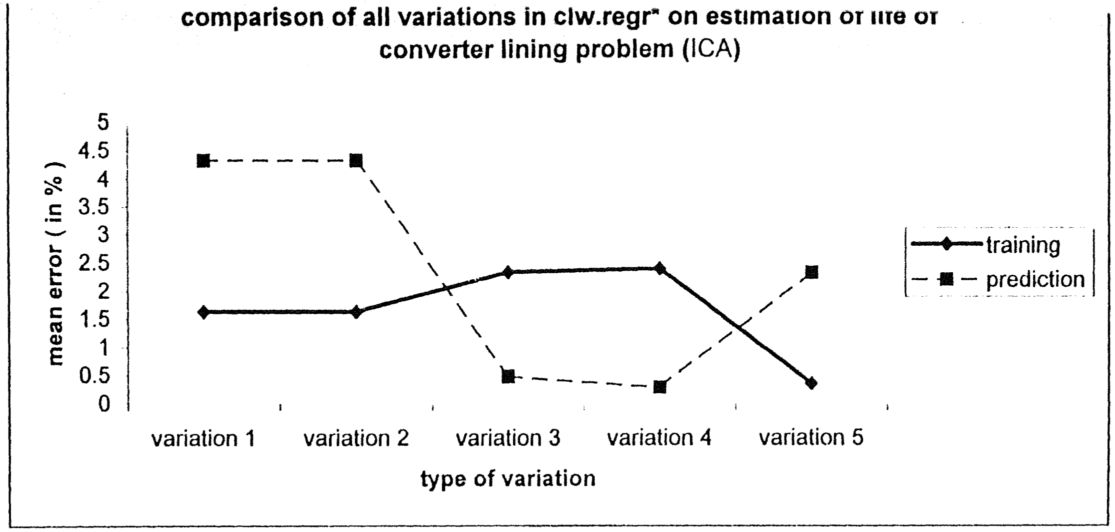

Fig 2.22 : comparison of all variations for clw.regr using SOM clustering with 3 clusters and exponential modeling function on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
type of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	1.63	0.03	0.5	0.81	3.58	0.49	1.02	4.33	0.19	3.06	0.12	4.44	4.21	1.04
variation 2	1.63	0.03	0.5	0.81	3.58	0.49	1.02	4.33	0.19	3.06	0.12	4.44	4.21	1.04
variation 3	2.34	0.06	0.67	0.53	3.32	0.84	0.98	0.48	0	0.35	0.1	0.59	0.38	1
variation 4	2.4	0.06	0.68	0.51	3.09	1.25	0.98	0.29	0	0.24	0.19	0.48	0.09	1
variation 5	0.35	0	0.15	0.42	1.57	0.06	1	2.32	0.06	1.68	0.5	2.82	1.82	1.02

Table 2.22 : comparison of all variations for clw.regr using SOM clustering with 3 clusters and exponential modeling function on estimation of life of converter lining problem (ICA)

* clw.regr means cluster wise regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

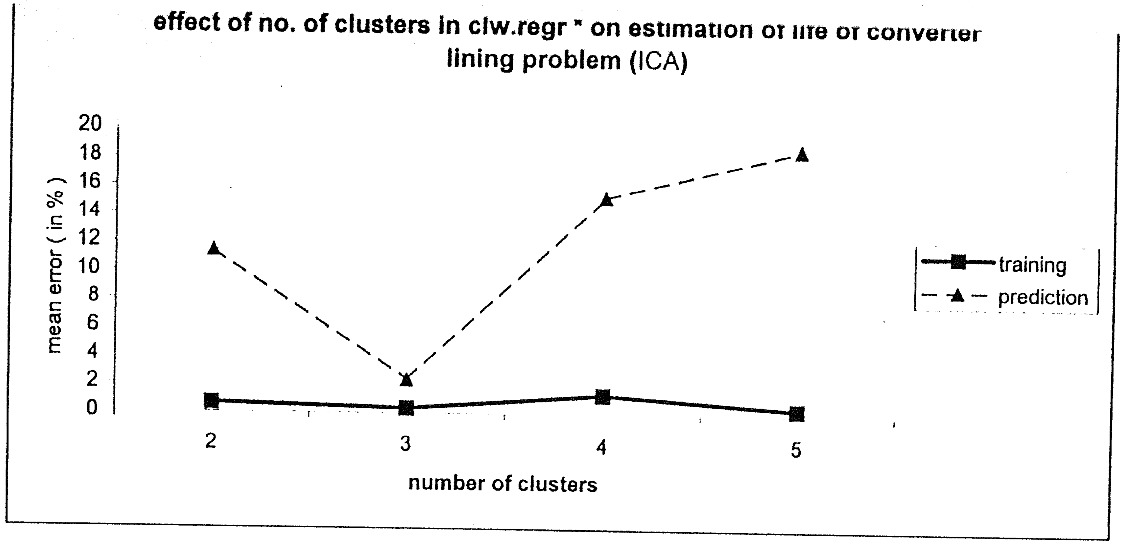

Fig 2.21 : effect of number of clusters in clw.regr variation 5 using SOM clustering with exponential modeling function on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
no. of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
2	0.68	0.01	0.27	0.67	2.06	0.03	1	11.41	2.21	10.52	9.55	20.96	1.86	1.1
3	0.35	0	0.15	0.42	1.57	0.06	1	2.32	0.06	1.68	0.5	2.82	1.82	1.02
4	1.33	0.05	0.6	1.69	5.74	0.01	1	15.25	2.8	11.83	6.88	22.13	8.37	1.15
5	0.36	0	0.17	0.49	1.76	0.01	1	18.6	4.71	15.35	11.21	29.8	7.39	1.19

Table 2.21 : effect of number of clusters for clw.regr variation 5 using SOM clustering with exponential modeling function on estimation of life of converter lining problem (ICA)

* clw.regr means cluster wise regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

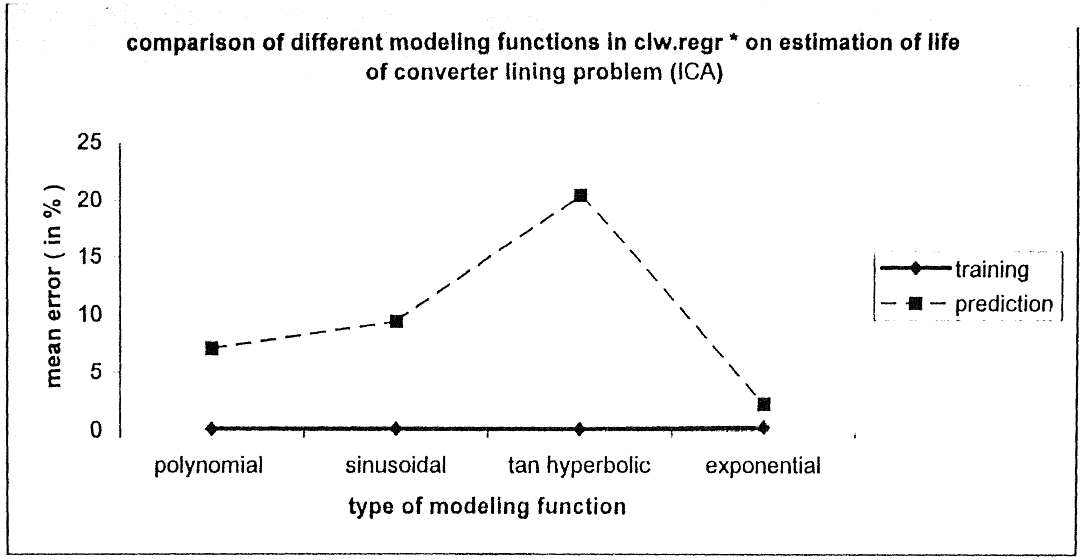

Fig 2.29: comparison of different modeling functions for clw.regr variation 5 using SOM clustering with 3 clusters on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
modeling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	0.16	0	0.06	0.14	0.55	0.01	1	7.1	0.63	5.61	3.56	10.66	3.54	0.96
sinusoidal	0.19	0	0.07	0.19	0.73	0.02	1	9.41	1.07	7.31	4.29	13.69	5.12	0.96
tan hyperbolic	0.17	0	0.06	0.14	0.55	0	1	20.4	6.22	17.64	14.35	34.76	6.05	0.86
exponential	0.35	0	0.15	0.42	1.57	0.06	1	2.32	0.06	1.68	0.5	2.82	1.82	1.02

Table 2.29: comparison of different modeling functions in clw.regr variation 5 using SOM clustering with 3 clusters on estimation of life of converter lining problem (ICA)

* clw.regr means cluster wise regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

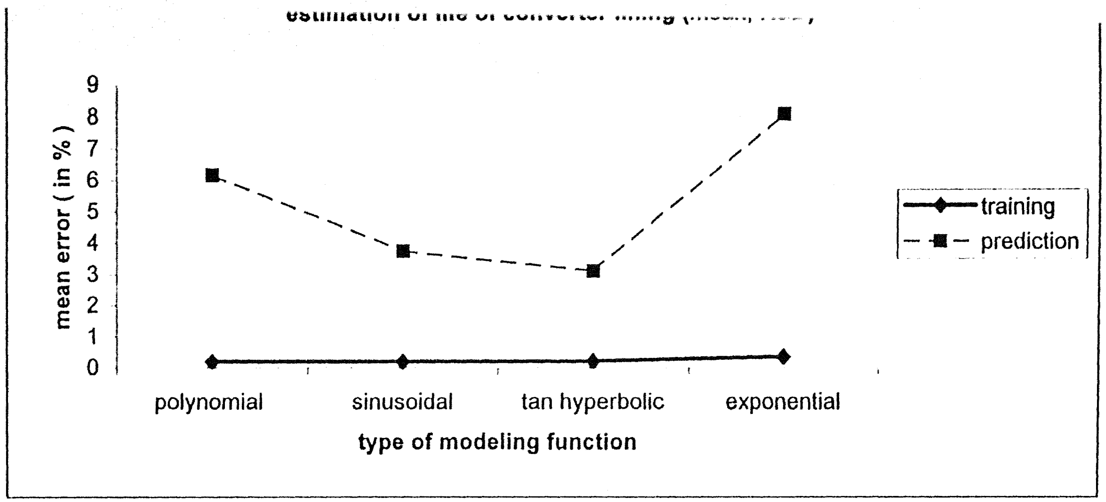

Figure 2.24 : comparison of different modeling functions in clw.regr variation 5 using SOM with 3 clusters on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
modeling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	0.2	0	0.08	0.18	0.62	0.02	1	6.17	0.76	6.17	6.16	12.34	0.01	1.06
sinusoidal	0.2	0	0.07	0.17	0.59	0.03	1	3.74	0.16	2.79	1.24	4.99	2.5	1.04
tan hyperbolic	0.21	0	0.08	0.19	0.65	0.03	1	3.1	0.13	2.59	1.94	5.04	1.15	1.03
exponential	0.34	0	0.13	0.34	1.24	0.02	1	8.07	1.14	7.55	6.99	15.06	1.08	1.08

Table 2.24: comparison of different modeling functions in clw.regr variation 5 using SOM with 3 clusters on problem of estimation of life of converter lining (mean, R&D)

*clw.regr means cluster wise regression
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

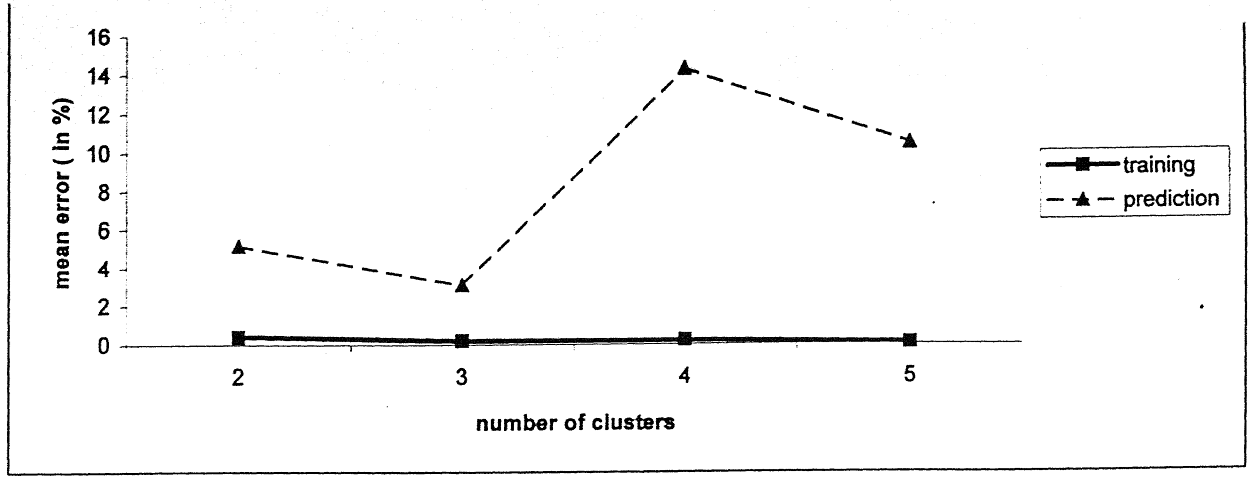

Fig 2.25: effect of number of clusters in clw.regr variation 5 using SOM clustering and tanh modeling function on estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
no of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
2	0.42	0	0.15	0.32	1.21	0.04	1	5.17	0.3	3.84	1.69	6.85	3.48	1.
3	0.21	0	0.08	0.19	0.65	0.03	1	3.1	0.13	2.59	1.94	5.04	1.15	1.
4	0.22	0	0.09	0.26	0.99	0.01	1	14.22	2.02	10.06	0.5	14.72	13.72	1.
5	0.09	0	0.03	0.08	0.35	0.02	1	10.41	1.11	7.44	1.57	11.98	8.84	1

Table 2.25: effect of number of clusters in clw.regr variation 5 usingSOM clustering and tanh modeling function on estimation of life of converter lining(mean, R&D)

* clw.regr means cluster wise regression
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

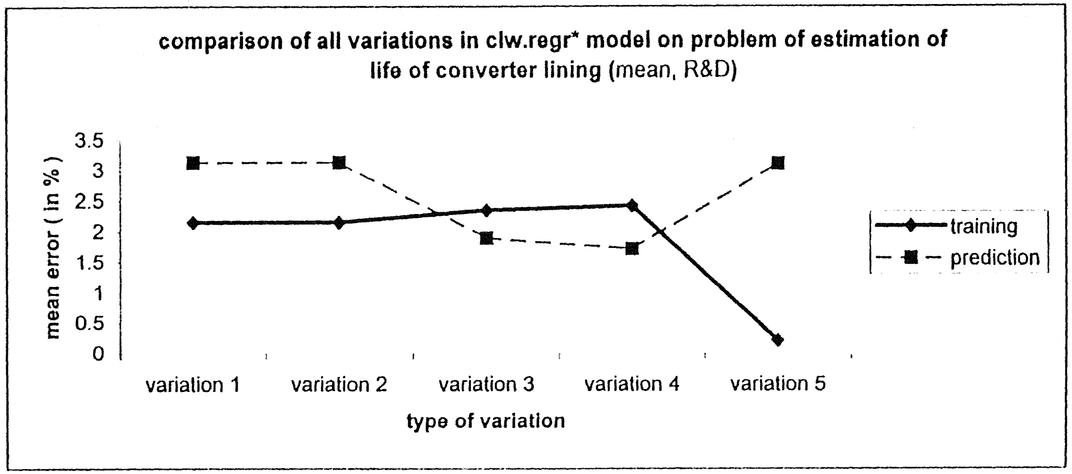

Fig 2.26 : comparison of all variations in clw.regr using SOM clustering with 3 clusters and tanh modeling function on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
ype of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	2.16	0.09	0.83	2.05	8.49	0.15	1.02	3.13	0.11	2.37	1.2	4.32	1.93	1.01
variation 2	2.16	0.09	0.83	2.05	8.49	0.15	1.02	3.13	0.11	2.37	1.2	4.32	1.93	1.01
variation 3	2.35	0.06	0.66	0.28	2.77	1.74	0.98	1.9	0.04	1.42	0.66	2.55	1.24	1.01
variation 4	2.42	0.06	0.68	0.31	2.95	2.02	0.98	1.71	0.03	1.27	0.55	2.27	1.16	1.01
variation 5	0.21	0	0.08	0.19	0.65	0.03	1	3.1	0.13	2.59	1.94	5.04	1.15	1.03

Table 2.26 : comparison of all variations in clw.regr using SOM clustering with 3 clusters and tanh modeling function on problem of estimation of life of converter lining (mean, R&D)

*clw.regr means cluster wise regression
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

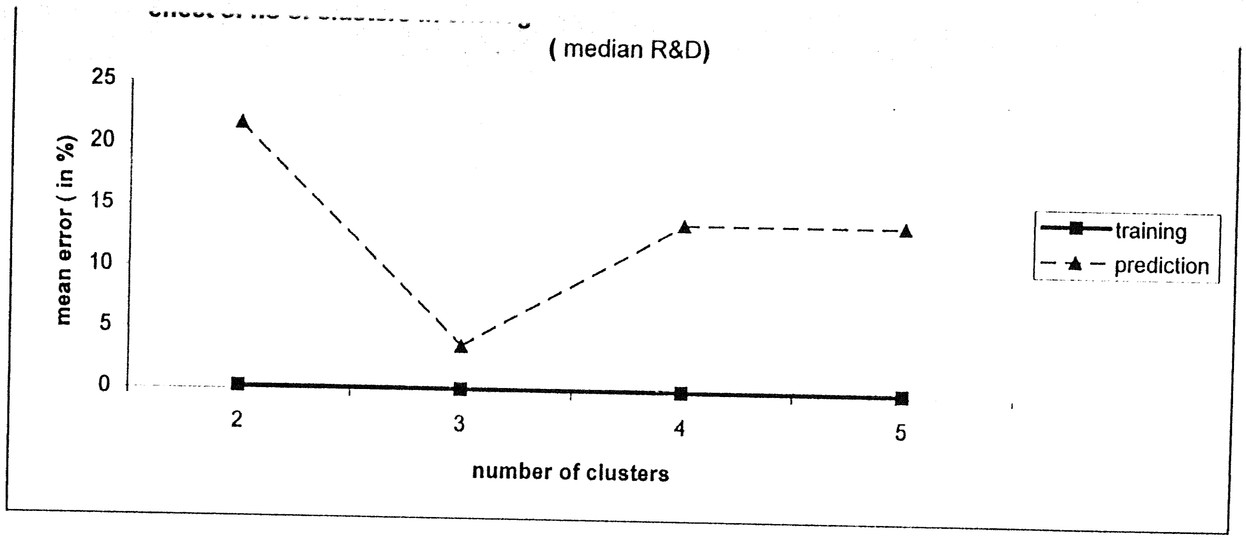

Fig 2.27: effect of number of clusters in clw.regr variation 5 using k-means clustering and tanh modeling function on estimation of life of converter lining (median, R&

	training statistics							prediction statistics						
no of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
2	0.25	0	0.11	0.3	1	0	1	21.66	4.7	15.34	1.06	22.72	20.6	1.22
3	0.2	0	0.08	0.19	0.61	0.01	1	3.7	0.24	3.47	3.23	6.93	0.47	1.03
4	0.17	0	0.06	0.12	0.4	0.02	1	13.75	2.21	10.52	5.69	19.44	8.06	0.94
5	0.13	0	0.05	0.12	0.4	0.02	1	13.75	2.21	10.52	5.69	19.44	8.06	0.94

Table 2.27: effect of number of clusters in clw.regr variation 5 using k-means clustering and tanh modeling function on estimation of life of converter lining(median, R&

* clw.regr means cluster wise regression
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

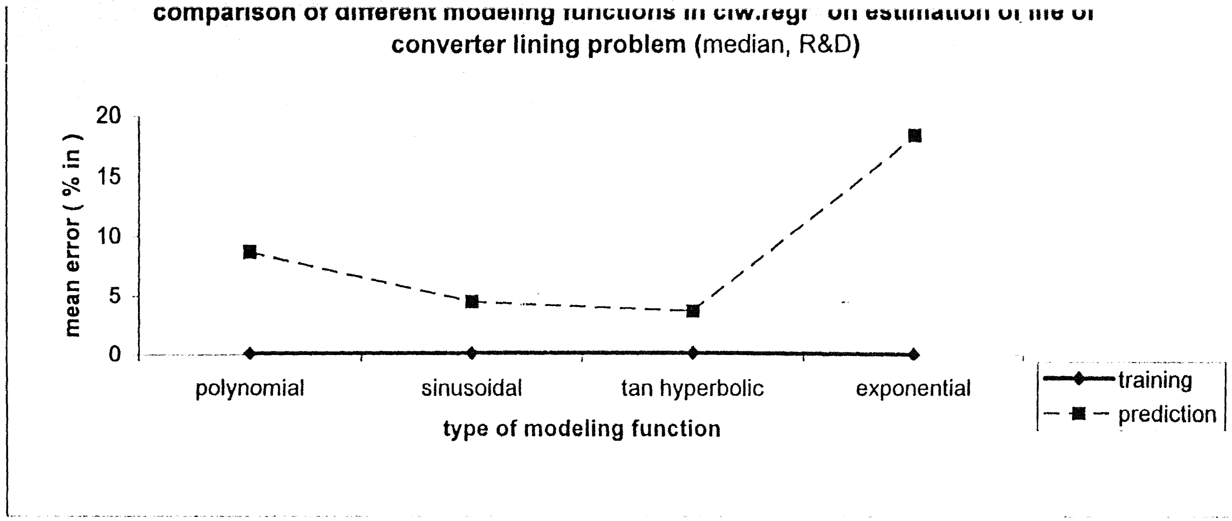

Fig 2.28 :comparison of all modeling functions in clw.regr variation 5 using k-means clustering with 3 clusters on estimation of life of converter lining problem (median, R&D)

	training statistics								prediction statistics						
modeling functon	mn error	ms error	rms error	error std	max error	min error	slope		mn error	ms error	rms error	error std	max error	min error	slope
polynomial	0.13	0	0.05	0.12	0.41	0.02	1		8.73	1.3	8.06	7.32	16.05	1.41	1.09
sinusoidal	0.17	0	0.07	0.16	0.54	0.03	1		4.54	0.23	3.35	1.38	5.92	3.16	1.05
tan hyperbolic	0.2	0	0.08	0.19	0.61	0.01	1		3.7	0.24	3.47	3.23	6.93	0.47	1.03
exponential	0.04	0	0.01	0.03	0.11	0	1		18.37	6.21	17.63	16.85	35.22	1.52	1.17

Table 2.28 : comparison of different modeling functions in clw.regr variation 5 using k-means clustering with 3 clusters on estimation of life of converter lining problem (median, R&D)

* clw.regr means cluster wise regression
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

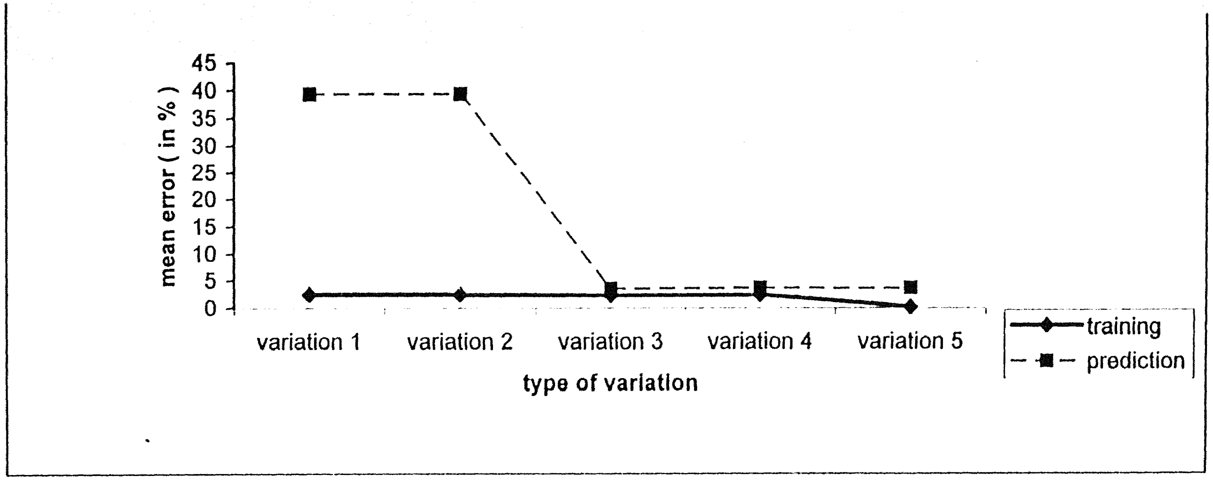

Fig 2.29: comparison of all variations in clw.regr model using k-means clustering with 3 clusters and tanh. modeling function on estimation of life of converter lining problem (median, R&D)

	training statistics								prediction statistics						
type of variation	mn error	ms error	rms error	error std	max error	min error	slope		mn error	ms error	rms error	error std	max error	min error	slo
variation 1	2.55	0.09	0.84	1.65	6.36	0.44	1.02		39.41	19.26	31.03	19.32	58.72	20.09	1.3
variation 2	2.55	0.09	0.84	1.65	6.36	0.44	1.02		39.41	19.26	31.03	19.32	58.72	20.09	1.3
variation 3	2.35	0.06	0.66	0.27	2.96	1.78	0.98		3.61	0.14	2.61	0.79	4.4	2.82	1.0
variation 4	2.42	0.06	0.68	0.29	2.98	1.86	0.98		3.73	0.14	2.68	0.68	4.42	3.05	1.0
variation 5	0.2	0	0.08	0.19	0.61	0.01	1		3.7	0.24	3.47	3.23	6.93	0.47	1.0

Table 2.29 : comparison of all variations in clw.regr model using k-means clustering with 3 clusters and tanh. modeling function on estimation of life of converter lining problem (median, R&D)

* clw.regr means cluster wise regression

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

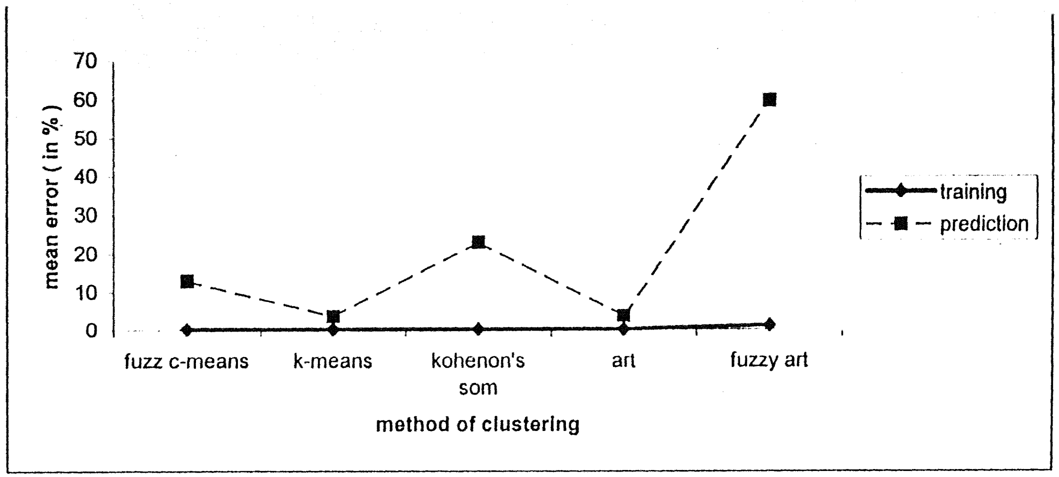

Fig 2.30 : comparison of different clustering methods in clw.regr variation 5 using tanh modeling function and 3 clusters on problem of estimation of life of converter lining (median R&D)

	training statistics							prediction statistics						
clustering method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
fuzz c-means	0.23	0	0.08	0.19	0.62	0.01	1	13.02	2.31	10.74	7.84	20.86	5.18	1.08
k-means	0.2	0	0.08	0.19	0.61	0.01	1	3.7	0.24	3.47	3.23	6.93	0.47	1.03
kohenon's som	0.22	0	0.08	0.21	0.66	0.02	1	23	5.56	16.67	5.14	28.15	17.86	0.77
art	0.21	0	0.08	0.19	0.61	0.01	1	3.79	0.24	3.47	3.23	6.93	0.47	1.03
fuzzy art	1.2	0.05	0.6	1.88	6.6	0.01	1	59.52	51.81	50.3	40.8	100	19.4	0.404

Table 2.30 : comparison of different clustering methods in clw.regr variation 5 using tanh modeling function and 3 clusters on problem of estimation of life of converter lining (median R&D)

* clw.regr means cluster wise regression
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

ı the graph it can be deduced that *exponential* modeling shows good performance for tion 5 when the data is divided into three clusters. The effect of number of clusters ıe variation 5 and SOM clustering with *exponential* modeling function is shown in 'ig 2.21 and Table 2.21, dividing the data into five clusters yields good training but a prediction. A comparison of all variations is brought out for the *exponential* mode- function with five clusters and SOM clustering method in the Table 2.21 and Fig , it can be observed that variation 4 has best performance with training error 2.4 and iction error 0.29

.esults of estimation of life of converter lining problem (mean, R&D)

For RD problem the results are given in Table C. Same trend can be observed in problem also as in the case of ICA. The best performance is given by variation 5 with e clusters using SOM to cluster and *tanh* modeling function, the training error is 0.21 the prediction error is 3.1. But the variation four also shows a good performance with ıing error 2.41 and prediction error 1.20. The modeling function used for this case is and the clustering method used is SOM with three clusters. The same trend of fuzzif- model having higher training error and lower prediction error is seen here. For this blem the effect of number of clusters is shown in Fig 2.25 and Table 2.25. From the ph it can be deduced that the division of data into three clusters gives a better perform- ;e for the model. From Fig 2.24 and Table 2.24 the effect of modeling functions can be ;erved. It can be deduced that the model with *tanh* modeling function has a better perf- nance. A comparison of all the variations is shown in the Fig 2.26 and Table 2.26.

Results of estimation of life of converter lining problem (median, R&D)

The results are given in the Table B. The best performance is shown by the vari- on 5 using *tanh* modeling function and K-mean clustering method with three clusters, ; training error is 0.2 and prediction error is 3.7. But with the variation 2 using *polyno- 'al* modeling function and K-mean clustering with two clusters has poorer training but ıod prediction, the training error is 3.99 where as the prediction error is 1.84. The effect 'number of clusters is shown in the Fig 2.27 and Table 2.27. From the graph one can ›serve that the division of the data into three clusters gives good results for the variation ve. The effect of modeling functions in variation 5 with three clusters using K mean cl- ;tering is given in the Fig 2.28 and Table 2.28, *tanh* and *sin* modeling functions give go- d results. A comparison of all the variations is shown in the Fig 2.29 and Table 2.29. inally a comparison of all the clustering methods is given in Fig 2.30 and Table 2.30. Fr-

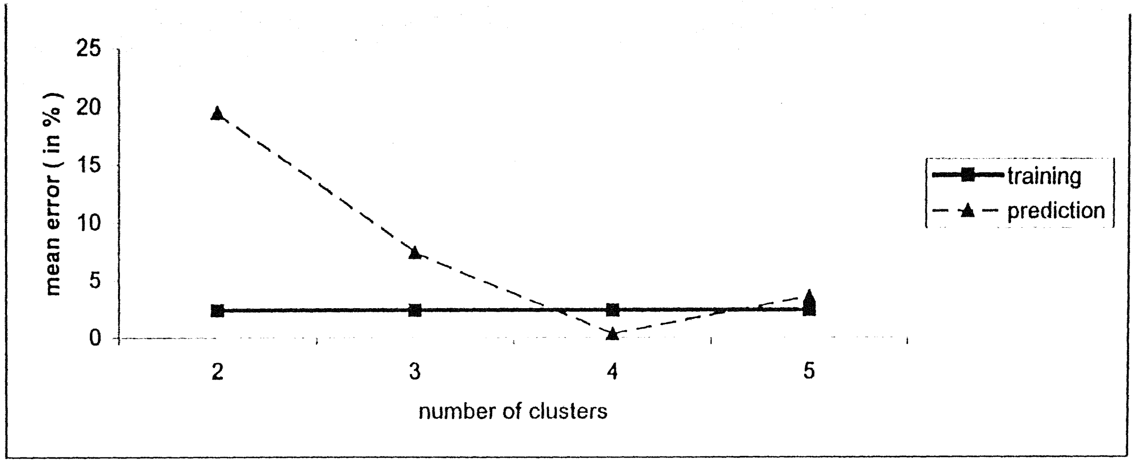

Fig 2.31 : effect of no. of clusters in clw.regr variation 3 using k-mean clustering and tanh modeling function on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
no.of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
2	2.38	0.06	0.67	0.42	2.91	1.39	0.98	19.53	3.83	13.84	1.29	20.82	18.23	1.2
3	2.39	0.06	0.66	0.11	2.62	2.19	0.98	7.38	0.69	5.87	3.79	11.17	3.58	1.04
4	2.4	0.06	0.67	0.13	2.62	2.16	0.98	0.33	0	0.32	0.31	0.65	0.02	1
5	2.4	0.06	0.67	0.07	2.52	2.27	0.98	3.58	0.21	3.28	2.94	6.52	0.65	1.04

Table 2.31 : effect of no. of clusters in clw.regr variation 3 using k-mean clustering and tanh modeling function on estimation of life of converter lining problem (PCA)

*clw.regr means cluster wise regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

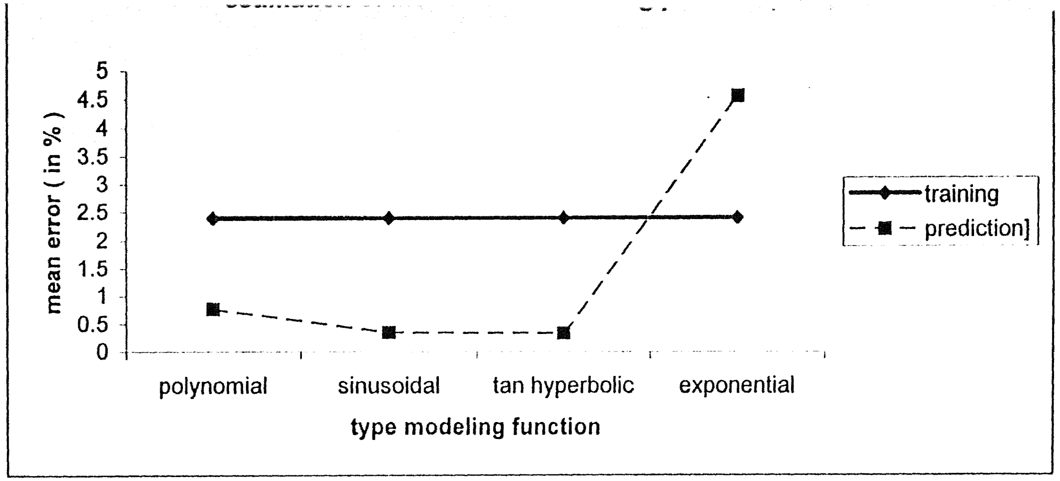

Fig 2.32 : comparison of different modeling functions in clw.regr variation 3 using k-mean clustering with 4 clusters on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
modling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	2.4	0.06	0.67	0.09	2.6	2.24	0.98	0.77	0.01	0.61	0.39	1.16	0.38	1.01
sinusoidal	2.4	0.06	0.67	0.11	2.62	2.19	0.98	0.35	0	0.27	0.17	0.52	0.18	1
tan hyperbolic	2.4	0.06	0.67	0.13	2.62	2.16	0.98	0.33	0	0.32	0.31	0.65	0.02	1
exponential	2.4	0.06	0.66	0.03	2.46	2.35	0.98	4.54	0.24	3.45	1.78	6.31	2.76	1.05

Table 2.32: comparison of different modeling functions in clw.regr variation 3 using k-mean clustering with 4 clusters on estimation of life of converter lining problem (PCA)

*clw.regr means cluster wise regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

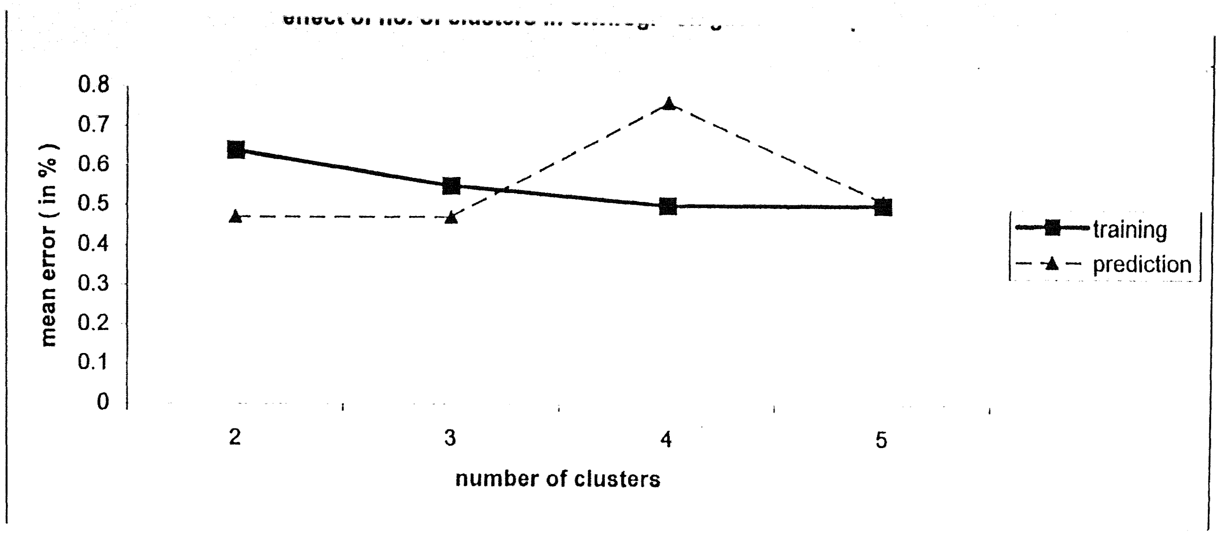

Fig 2.34 : effect of number of clusters in clw.regr using k-means clustering variation 5 and exponential modeling function on modeling of Box Jenkins' gas furnace problem

	training statistics							prediction statistics						
no. of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
2	0.64	0.01	0.05	0.53	3.5	0.01	1	0.47	0	0.34	0.08	0.55	0.4	1
3	0.55	0.01	0.04	0.47	3.24	0	1	0.47	0	0.42	0.36	0.83	0.11	1
4	0.5	0	0.04	0.43	3.36	0	1	0.76	0.01	0.53	0.02	0.77	0.74	1
5	0.5	0	0.04	0.4	2.96	0	1	0.51	0	0.36	0.01	0.52	0.49	1

Table 2.34 : effect of number of clusters in clw.regr using k-means clustering variation 5 and exponential modeling function on modeling of Box Jenkins' gas furnace problem

* clw.regr means cluster wise regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error

shaded row represents the best performance

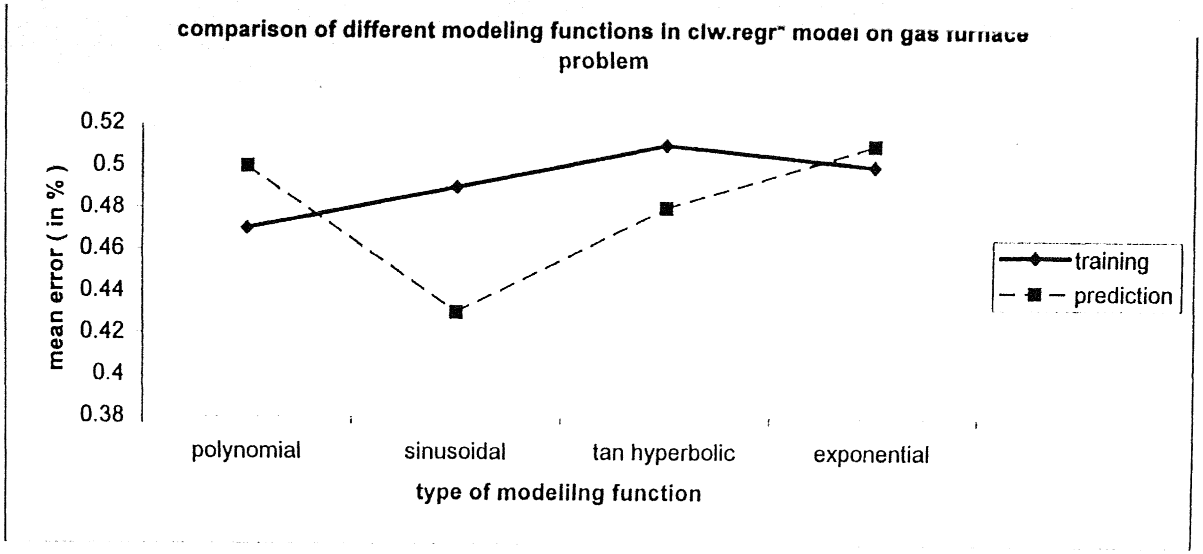

Fig 2.35 : comparison of different modeling functions in clw.regr variation 5 using k-means clustering with 5 clusters on modeling of Box Jenkins' gas furnace

	training statistics							prediction statistics						
modeling function	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
polynomial	0.47	0	0.04	0.43	3.33	0.01	1	0.5	0	0.36	0.08	0.58	0.42	1
sinusoidal	0.49	0	0.04	0.44	3.26	0.01	1	0.43	0	0.3	0.04	0.46	0.39	1
tan hyperbolic	0.51	0	0.04	0.44	3.12	0	1	0.48	0	0.36	0.19	0.67	0.29	1
exponential	0.5	0	0.04	0.4	2.96	0	1	0.51	0	0.36	0.01	0.52	0.49	1

Table 2.35 : comparison of different modeling functions in clw.regr variation 5 using k-means clustering with 5 clusters on modeling of Box Jenkins' gas furnace

* clw.regr means cluster wise regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

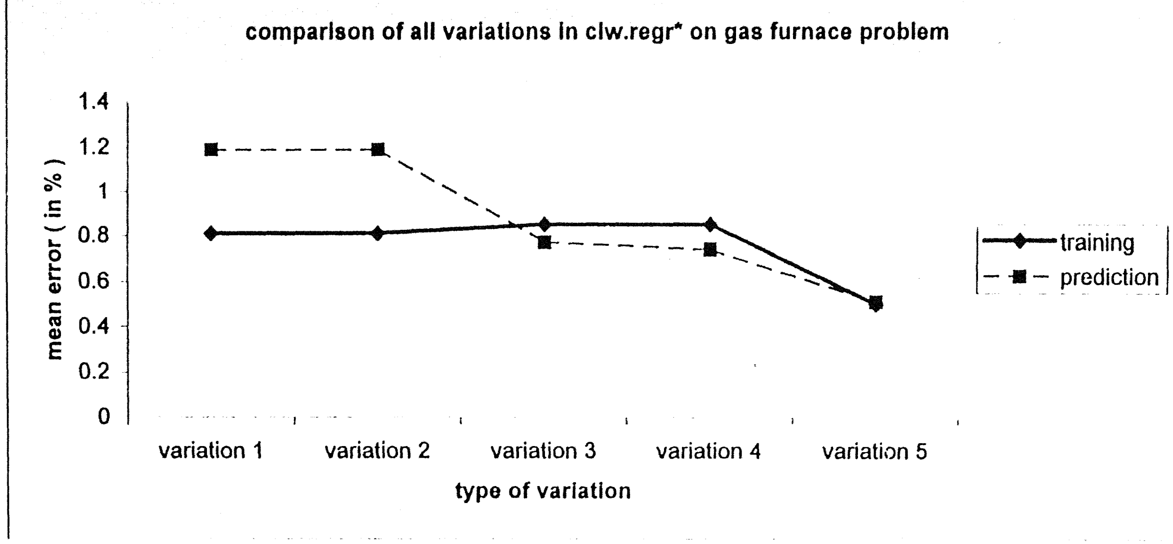

Fig 2.36 : comparison of different modeling functions in clw.regr variation 5 using k-means clustering with 5 clusters on modeling of Box Jenkins' gas furnace problem

	training statistics							prediction statistics						
type of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	0.81	0.01	0.06	0.61	2.97	0	1.01	1.19	0.02	0.95	0.62	1.81	0.57	1.01
variation 2	0.81	0.01	0.06	0.61	2.97	0	1.01	1.19	0.02	0.95	0.62	1.81	0.57	1.01
variation 3	0.85	0.01	0.06	0.55	3.73	0	0.99	0.77	0.01	0.65	0.5	1.28	0.27	0.99
variation 4	0.85	0.01	0.06	0.55	3.77	0	0.99	0.74	0.01	0.63	0.5	1.24	0.23	0.99
variation 5	0.5	0	0.04	0.4	2.96	0	1	0.51	0	0.36	0.01	0.52	0.49	1

Table 2.36 : comparison of different modeling functions in clw.regr variation 5 using k-means clustering with 5 clusters on modeling of Box Jenkins' gas furnace problem

* clw.regr means cluster wise regression modeling
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimum error
shaded row represents the best performance

ı the table it can be seen that the K-means clustering method is showing better perform-ce of all clustering methods.

, **Results of estimation of life of converter lining problem (PCA)**

From the results given in the Table D, it can be observed that variation 3 with *tanh* odeling function using the K-means clustering with three clusters, the training error is 39 and prediction error is 0.33. But one can observe that variation 1 with polynomial odeling function and fuzzy C-means clustering with five clusters has a training error 65 and prediction error 1.51. It can be seen that with the som clustering also with five usters and *exponential* modeling function the training error is 2.38 and the prediction ror is 1.39. The effect of number of clusters on the problem of PCA is shown in the g 2.31 and Table 2.31. From the graph one can observe that the division of the data into ›ur clusters gives good results for the variation 3. The effect of modeling functions in ıriation 3 with four clusters using K-means clustering is given in the Fig 2.32 and Table 32. A comparison of all the variations is shown in the Fig 2.33 and Table 2.33.

.3.3.5 Results of modeling of Box Jenkins' gas furnace problem

The results are given in Table E. From the results it can be observed that variation using simple polynomial function with fuzzy C-mean clustering with four clusters ıows better performance, the training error is 0.47 and the prediction error is 0.44. The ıme trend as earlier, can be observed with this problem also. The effect of number f clusters is shown in the Fig 2.34 and Table 2.34. From the graph one can observe that ivision of the data into five clusters gives good results for the variation 5 using *exponent-ıl* modeling function. The effect of modeling functions in variation 5 with five clusters sing K-means clustering is given in the Fig 2.35 and Table 2.35. A comparison of all the 'ariations is shown in the Fig 2.36 and Table 2.36.

:.3.4 Conclusions

In this present work, the cluster wise fuzzy regression analysis is presented. The ›rocedure presented in section generalizes methods of Diamond[1]. As the classification lepends on the underlying principles of each clustering algorithm, the results heavily dep-end on the chosen clustering algorithms[2]. Based on numerical experiments, K-mean :lustering algorithm is recommended. The modeling functions have considerable effect ıpon the performance of each model. The choice of modeling function has to be made ba-sing on the input data pattern. For *sin, tanh,* and *exponential* the scaling does act an impo-rtant role. For a system having low complexity like Box data, the clustering does not show

impact upon the performance of the model. SOM clustering method though shows d performance, its ability to classify the data is very sensitive to the variations in α.

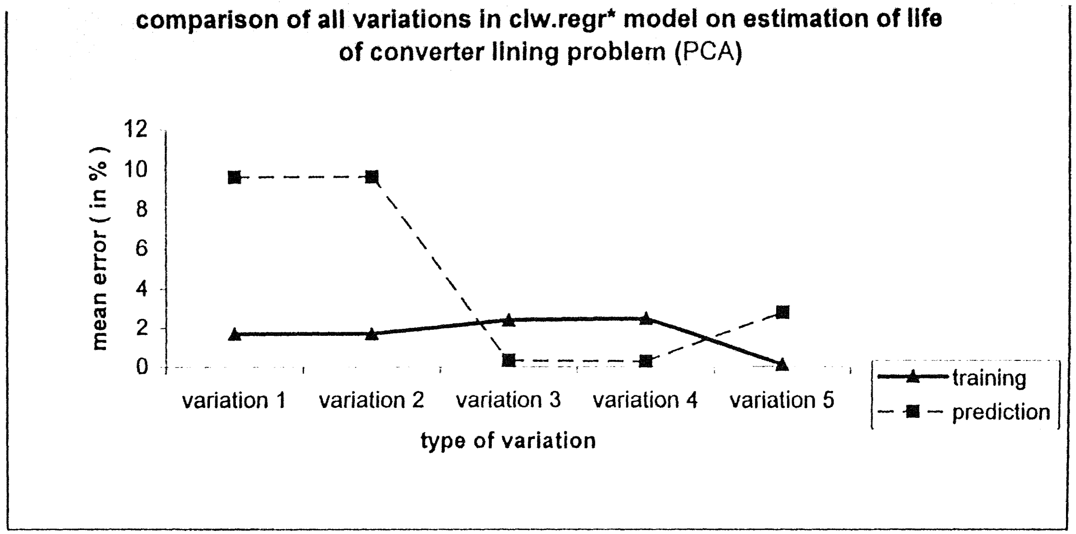

Fig 2.33 : comparison of all variations in clw.regr using k-means clustering with 4 clusters and tanh modeling function on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
type of variation	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
variation 1	1.69	0.04	0.54	0.94	3.1	0.11	1.02	9.63	1.19	7.71	5.12	14.74	4.51	1.05
variation 2	1.69	0.04	0.54	0.94	3.1	0.11	1.02	9.63	1.19	7.71	5.12	14.74	4.51	1.05
variation 3	2.4	0.06	0.67	0.13	2.62	2.16	0.98	0.33	0	0.32	0.31	0.65	0.02	1
variation 4	2.46	0.06	0.69	0.31	3.05	1.74	0.98	0.29	0	0.26	0.22	0.51	0.06	1
variation 5	0.11	0	0.04	0.07	0.24	0.02	1	2.78	0.08	1.98	0.34	3.12	2.44	1.03

Table 2.33 : comparison of all variations in clw.regr using k-means clustering with 4 clusters and tanh modeling function on estimation of life of converter lining problem (PCA)

*clw.regr means cluster wise regression model
mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error
shaded row represents the best performance

Chapter 3

3.1 Sugeno-type fuzzy identification method

3.1.1 Introduction

Sugeno-type fuzzy identification method [4] is a mathematical tool to build a fuzzy model of a system where fuzzy implications and reasoning are used. The premise of an implication is the description of fuzzy subspace of inputs and its consequence is a linear input-output relation. In the present work, the Sugeno-type fuzzy identification is simply implemented for the test problems, and results are discussed.

3.1.2 Implementation of the method

Implementation of the Sugeno-type fuzzy identification involves the following steps.

Step (i) : Preprocess or Scale the data

Step (ii) : At layer one assume an input variable as premise variable and divide the input space.

Step (iii) : Evaluate the consequent parameters through recursive least square regression, for every premise.

Step (iv) : Premise parameters are readjusted iteratively by *complex* algorithm

Step (v) : Evaluate the performance index for the premise variable

Step (vi) : Keep the variable giving the least performance as premise variable for the layer one and proceed for the next layer.

Step (vii) : Repeat from step (ii) to step (vi) till the required performance is not achieved.

Details of each step is given in [4].

3.1.3 Result and Discussion

For all the problems the data is scaled between 0 to 1 using the previously mentioned scaling technique. From the results given in Table 3.1 and Fig 3.1 it can be seen that the training is better but the prediction is worse, i.e. in the case of estimation of life of converter lining (ICA), the training error is 2.1 where as the prediction error is 3.8.

In this problem the number of maximum layers is kept as 2. For the case of Box data the training as well as predictions are good. The results of Box data is matched with the results given in [3].

3.2 Orthogonal parameter estimation technique

3.2.1 Introduction

In orthogonal parameter estimation[5], the premise of the model is first determined using a fuzzy discretization technique by constructing reference fuzzy sets. This amounts to the partition of the input space, as has been done in the previous methods. The number of reference fuzzy sets determines the number of rules and numbers linear equations in the consequent part of the model. The parameters of these linear equations are then estimated using an orthogonal estimator. The present work studies the effect of clustering method upon the performance of the of each model.

3.2.2 Formulation of Ortho-Clustering Technique

Steps involved in modeling the system through ortho-clustering technique are as follows

Step (i) : Preprocess or Transform (Scale) the data

Step (ii) : Classify the input space for premise identification

Step (iii) : Formulate [ϕ] and [y] from the identified premises

Step (iv) : Estimate model parameters through orthogonal least square regression

Details of each step is given below

Step (ii) Classification of Input Space

The premise model of the system is determined using the fuzzy discretization technique by constructing the reference fuzzy sets through a suitable clustering algorithm. Clustering methods used for dividing the input space are

1. Fuzzy c-means clustering

2. k-means clustering

3.self organizing map (SOM) clustering

4.Adaptive Resonance Theory 2 (ART 2) clustering

5.fuzzy Adaptive Resonance Theory (fuzzy ART) clustering.

) (iii) Formulation of [ϕ], [y]

Given an input $\{u^k_1 ,.......,u^k_r \}$, The discretized form of a input variable u_l is essed as $[\mu^k_{11} , \mu^k_{21} , ...\mu^k_{l1}]^T$ where l denotes the number of reference fuzzy sets vell as number of rules constitut-ing the model [5].then the total output of the model if-erred by taking the weighted average of the local outputs $(y^k_1 , ..., y^k_1)$

$$Y_k = \phi^T_k 6$$

ere

$$[b_{10}..b_{l1}, b_{11}..b_{l1},.........b_{lr}]^T$$
$$= [v^k_1,...v^k_l, v^k_1 u^k_1,.....v^k_l u^k_r]$$

he above equation [θ] is the vector of parameters of the model and v can be culated as

$$v^k_i = \frac{\xi^k_i}{\sum_{i=1}^{l} \xi^k_i}$$

ere $\xi^k_i = \mu^k_{i1} \cap \mu^k_{i2}............\mu^k_{ir}$

ep (iv) Estimation of parameters of the model

To determine which terms to include in the above equation and then estimate their rameters, the step wise regression procedure, along with the orthogonal least-square gorithm [13],[12] is used. The basic idea of this algorithm is to transfer the following uation into an equivalent orthogonal equation

$$Y_k = \phi^T_k 6$$

o equivalent orthogonal equation

$$= \sum_{i=1}^{(r+1)l} w_{ik} g_i$$

here the w_{ik}'s are orthogonal to one another, with

$_{1k}=f_{1k}$

$_{mk}=f_{mk}-\sum_{i=1}^{m-1} \alpha_{im} w_{ik}$, m=2,3,.......,(r+1)*1

$$_j = \frac{\sum_{k=2}^{N} w_{ik} f_{jk}}{\sum_{k=1}^{N} w_{ik}^2}, \quad I<j,\ j=2,3,\ldots\ldots\ldots,(r+1)*l.$$

ıe estimates of the coefficients g_i are given by

$$_i = \frac{\sum_{k=1}^{N} w_{ik} y_k}{\sum_{k=1}^{N} w_{ik}^2}, \quad I=1,2,\ldots\ldots\ldots,(r+1)*l.\backslash$$

he coefficients of the original equation can easily be obtained according to the formulas

$$_{(r+1)*l} = \hat{g}_{(r+1)*l}$$

$$_i = \hat{g}_i - \sum_{j=i+1}^{(r+1)*l} \alpha_{ij} \hat{\theta}_j,$$

=(r+1)*l-1,(r+1)*l-2,....,1.

)efine the error reduction ratio due to the ith term as

$$err]_I = \frac{\hat{g}_i^2 \sum_{k=1}^{N} w_{ik}^2}{\sum_{k=1}^{N} y_k^2}$$

Γhus the significant terms can be chosen if their error reduction ratio is greater that some hreshold value. The procedure for transforming the f_{ik}'s to w_{ik}'s is given below (Gram-Schmidt orthogonalization [13]).

ɪn the first step, all the f_{ik}, i=1,2,.....,(r+1)*l are considered are possible candidates for w_{1k}. . For i=1,2,...,(r+1)*l, calculate

$$\hat{g}_1^{(i)} = \frac{\sum_{k=1}^{N} w_{1k}^{(i)} y_k}{\sum_{k=1}^{N} (w_{1k}^{2})^2}$$

$$rr]_1^{(i)} = \frac{(\hat{g}_1^{(i)})^2 \sum_{k=1}^{N} (w_{1k}^{(i)})^2}{\sum_{k=1}^{N} y_k^2}.$$

nd the maximum of $[err]_1^{(i)}$, say, $[err]_1^{(p)}=\max\{[err]_1^{(i)}, 1\leq i\leq (r+1)*l\}$. then the first term $_{1k}= w_{1k}^{(p)}$ is select with

$$= \hat{g}_1^{(p)} \quad and [err]_1 = [err]_1^{(p)}.$$

. the second step, all the f_{ik}, $i=1,2,\ldots,(r+1)*l$, $i\neq p$, are considered as possible candidates r w_{2k}. for $I=1,2,\ldots,(r+1)*l$, $i\neq p$, calculate

$$w_{2k}^{(i)} = f_{ik} - \alpha_{12}^{(i)} w_{1k}, \quad \hat{g}_2^{(i)} = \frac{\sum_{k=1}^{N} w_{2k}^{(i)} y_k}{\sum_{k=1}^{N} (w_{2k}^{(i)})^2}$$

$$err]_2^{(i)} = \frac{(\hat{g}_2^{(i)})^2 \sum_{k=1}^{N} (w_{2k}^{(i)})^2}{\sum_{k=1}^{N} y_k^2}$$

vhere

$$\alpha_{12}^{(i)} = \frac{\sum_{k=2}^{N} w_{1k} f_{ik}}{\sum_{k=1}^{N} w_{1k}^2}, \quad i<j,\ j=2,3,\ldots\ldots\ldots,(r+1)*l.$$

Find the maximum of $[err]_2^{(i)}$, say, $[err]_2^{(q)}= \max\{[err]_2^{(i)}, 1\leq i\leq (r+1)*l, i\neq p\}$. Then the second term $w_{2k}=w_{2k}^{(p)}=p_{qk}=\alpha_{12}w_{1k}$ is selected with

$$\alpha_{12} = \alpha_{12}^{(q)}, \quad \hat{g}_2 = \hat{g}_2^{(q)} \quad \text{and } [err]_2=[err]_2^{(q)}.$$

The same procedure will be repeated and terminated at the M_s *th* step when

$$1-\sum_{i=1}^{M_s}[err]_i < \rho$$

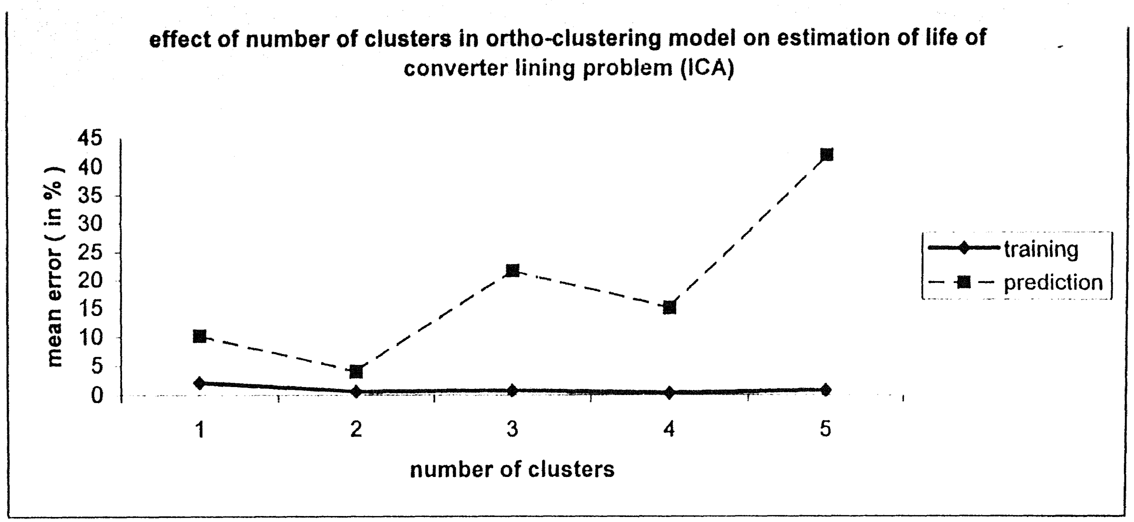

Fig 3.2 : effect of no. of clusters in ortho-clustering model using k-mean clustering and epsilon=0.001 on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
no. of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
1	2.18	0.08	0.78	1.8	5.61	0.39	1	10.24	1.3	8.06	5.01	15.25	5.24	0.95
2	0.64	0.01	0.27	0.74	2.47	0	1	4.04	0.28	3.77	3.48	7.53	0.56	0.97
3	0.82	0.02	0.43	1.32	4.97	0.01	1	21.68	8.18	20.22	18.66	40.33	3.02	1.22
4	0.4	0	0.15	0.35	1.23	0.01	1	15.12	2.33	10.8	2.17	17.29	12.95	0.98
5	0.88	0.03	0.46	1.39	4.59	0	1	41.95	25.78	35.9	28.6	70.55	13.35	0.58

Table 3.2 : effect of no. of clusters in ortho-clustering model using k-mean clustering and epsilon=0.001 on estimation of life of converter lining problem (ICA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

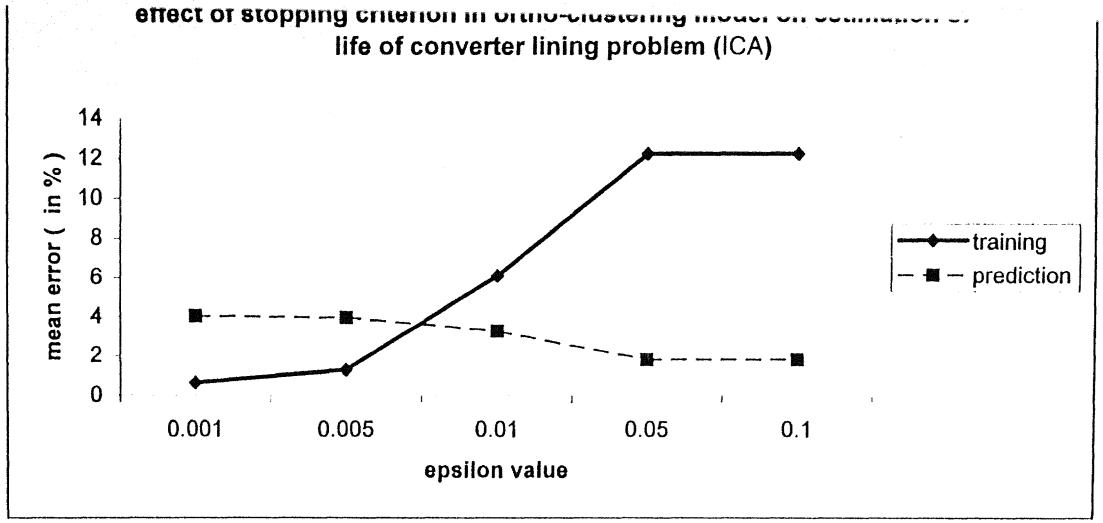

Fig 3.3: effect of stopping criterion for ortho-clustering model using k-mean clustering with [illegible] clusters on estimation of life of converter lining problem (ICA)

	training statistics							prediction statistics						
value of epsilon	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
0.001	0.64	0.01	0.27	0.74	2.47	0	1	4.04	0.28	3.77	3.48	7.53	0.56	0.97
0.005	1.28	0.03	0.45	1.03	3.64	0.13	1	3.95	0.28	3.77	3.57	7.52	0.38	0.96
0.01	6.09	0.79	2.47	6.51	21.09	0.12	1.01	3.27	0.19	3.09	2.9	6.17	0.36	1.03
0.05	12.23	1.93	3.86	6.63	24.88	0.36	1.02	1.8	0.03	1.27	0.1	1.9	1.69	1
0.1	12.23	1.93	3.86	6.63	24.88	0.36	1.02	1.8	0.03	1.27	0.1	1.9	1.69	1

Table 3.3 : effect of stopping criterion for ortho-clustering model using k-mean clustering with [illegible] clusters on estimation of life of converter lining problem (ICA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

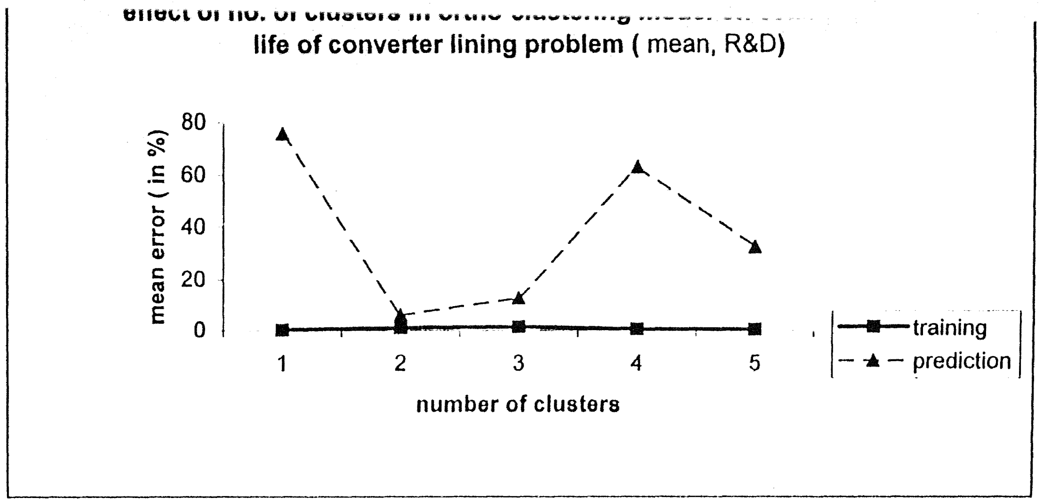

Fig 3.4 : effect of number of clusters in ortho-clustering model with k-means clustering and epsilon=0.001 on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
number of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
1	0.34	0	0.11	0.22	0.81	0.13	1	75.82	58.97	54.3	12.19	88.01	63.62	1.12
2	1.29	0.04	0.57	1.61	5.3	0.01	1	6.08	0.45	4.72	2.74	8.82	3.34	0.94
3	1.61	0.04	0.54	1.07	4.12	0.46	1	12.75	2.64	11.5	10.1	22.85	2.65	0.87
4	0.6	0.01	0.21	0.48	1.84	0.05	1	62.99	42.13	45.89	15.64	78.63	47.36	0.84
5	0.47	0.01	0.23	0.68	2.52	0	1	32.54	13.2	25.69	16.17	48.7	16.37	1.33

Table 3.4 : effect of number of clusters in ortho-clustering model with k-means clustering and epsilon=0.001 on problem of estimation of life of converter lining (mean, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

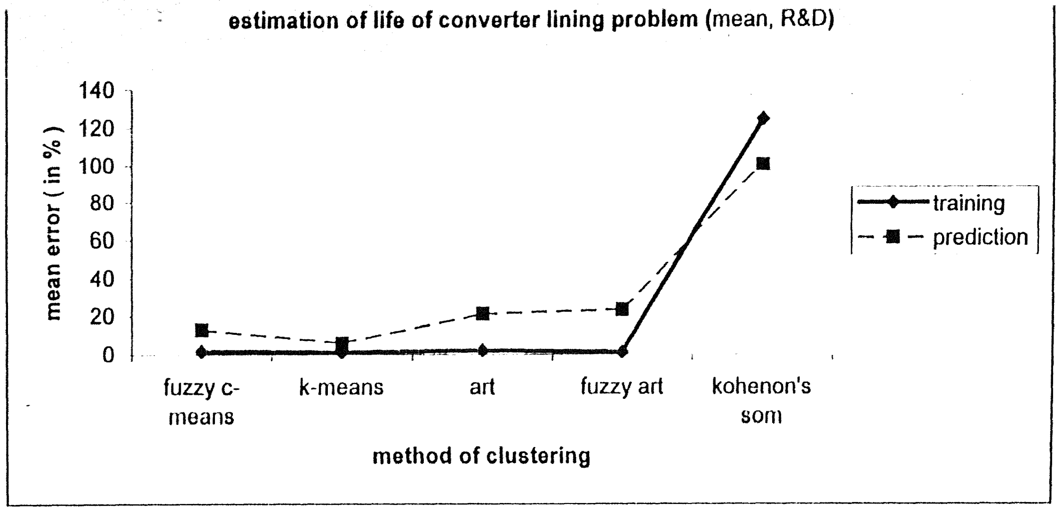

Fig 3.5: comparison of different methods of clustering in ortho-clustering model with 2 clustres and epsilon=0.001 on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
clustering method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	mn error	slope
fuzzy c-means	1.76	0.05	0.62	1.37	5.55	0.17	1	13.14	1.95	9.87	4.72	17.86	8.42	1.05
k-means	1.29	0.04	0.57	1.61	5.3	0.01	1	6.08	0.45	4.72	2.74	8.82	3.34	0.94
art	2.17	0.07	0.75	1.61	6.7	0.14	1	21.3	7.2	18.3	15.3	36.4	7.3	1.32
fuzzy art	1.41	0	0.097	0.25	0.93	0.014	1	23.4	6.23	17.3	23.3	25.9	16.4	0.98
kohenon's som	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.68

Table 3.5: comparison of different methods of clustering in ortho-clustering model with 2 clustres and epsilon=0.001 on problem of estimation of life of converter lining (mean, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

where ρ is a chosen tolerance. This gives rise to a subset model containing M_s significant terms.

3.2.3 Results and discussion

As described in chapter 3, various models are developed using different clustering methods. For each clustering method the slopping criterion , epsilon is varied between 0.001 to 0.1. The results for epsilon 0.001, 0.005, 0.01, 0.1 are noted. Also the number of cluster formed also varied between one to five. The parameters for the SOM, ART2 and fuzzy ART are as follows. As the data is scaled between zero to one for every problem the parameters remain the same. For the SOM the neighborhood size is varied between 0 to (number of clusters -1), the period is kept as 5 and the maximum limit of iterations is kept as 75. The factor α is kept 0.15. For ART2 the vigilance factor is varied between 0.9 to 0.6 and optimum value is found to be 0.8 .For fuzzy ART the vigilance factor is varied between 0.5 to 0.99 and the optimum value is found as 0.6. The factor α, and β are kept as 0.18 and 0.5 as per the specification in [14].

3.2.3.1 Results of estimation of converter lining problem

. Results of estimation of converter lining problem (ICA)

From the results tabulated in Table A, one can observe that the division of data set into two clusters using k-means clustering technique and keeping the stopping criterion epsilon = 0.001 gives best performance with training error of 0.64 and prediction error of 4.04. The effect of division of data can be observed in the Fig 3.2 and Table3.2. that the training error decreases as the number of clusters increase. But from the statistics of the prediction, it can be deduced that the division of data into two clusters gives good performance, increasing the number of clusters beyond two results in worse performance. The effect of stopping criterion can be observed in Fig 3.3 and Table 3.3 that the training error increases with increase of epsilon, but the prediction is better with the epsilon value equal to 0.1 and over all performance is better with 0.001.

i. Results of estimation of converter lining problem (mean, R&D)

The results are given in the Table C . From the results it can be seen that having two clusters using k-means clustering method and keeping stopping criterion as 0.005, i.e. the training error is 1.29 and prediction error is 6.08. From the Fig 3.4 and Table 3.4 it can be deduced that the division of data into two clusters gives good performance, increasing the number of clusters beyond two results in worse performance. The comparison in the performance of different clustering methods is brought out in Fig 3.5 and Table 3.5. Fuz-

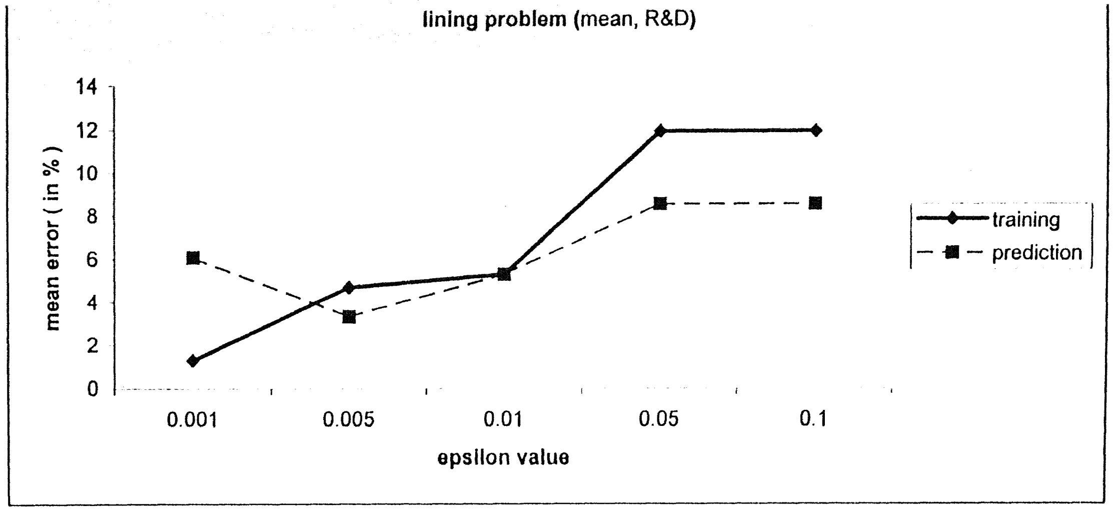

Fig 3.6 : effect of stopping criterion in ortho-clustering using k-mean clustering with 2 clusters on problem of estimation of life of converter lining (mean, R&D)

	training statistics							prediction statistics						
epsilon value	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
0.001	1.29	0.04	0.57	1.61	5.3	0.01	1	6.08	0.45	4.72	2.74	8.82	3.34	0.94
0.005	4.68	0.34	1.61	3.43	14.24	0.36	1	3.31	0.11	2.34	0.07	3.37	3.24	1
0.01	5.28	0.54	2.03	5.06	18.93	0.36	1	5.29	0.32	3.98	1.92	7.22	3.37	1.02
0.05	11.92	2	3.92	7.58	24.15	0.69	1.02	8.54	0.75	6.11	1.32	9.86	7.22	1.09
0.1	11.92	2	3.92	7.58	24.15	0.69	1.02	8.54	0.75	6.11	1.32	9.86	7.22	1.09

Table 3.6 : effect of stopping criterion in ortho-clustering using k-mean clustering with 2 clusters on problem of estimation of life of converter lining (mean, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

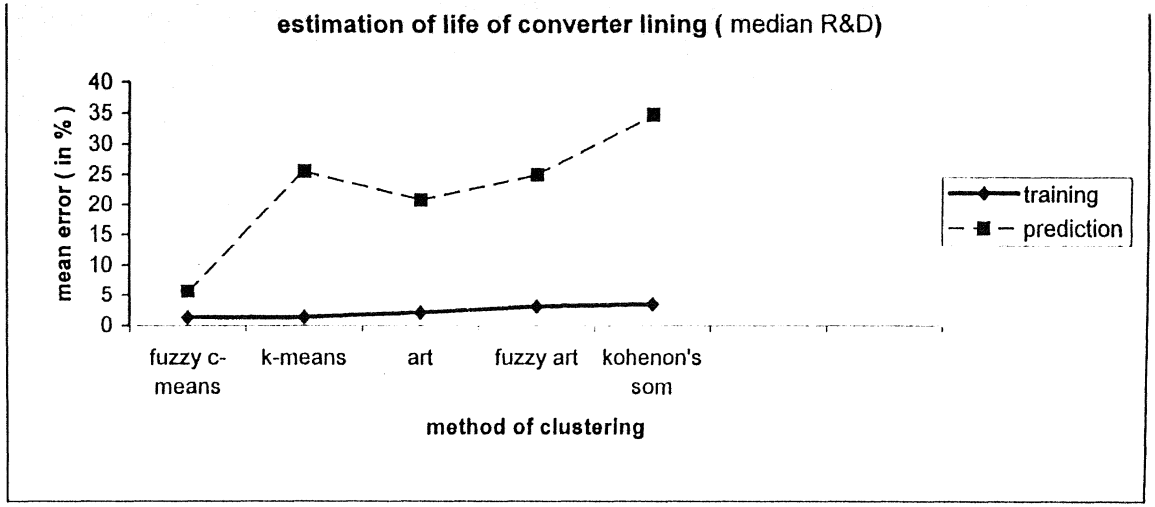

Fig 3.7 : comparison of different clustering methods in ortho-clustering model using 2 clusters and epsilon=0.001 on estimation of life of converter lining problem (median, R&D)

	training statistics							prediction statistics						
method of clustering	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
fuzzy c-means	1.36	0.03	0.5	1.19	3.68	0.04	1	5.67	0.53	5.15	4.57	10.24	1.09	1.06
k-means	1.4	0.05	0.63	1.79	5.79	0.01	1	25.5	6.91	18.58	6.35	31.86	19.15	1.26
kohenon's som	3.5	0.15	1.13	2.3	8.91	0.9	1.03	34.7	12.1	24.6	13.66	36.32	7.45	1.45
art	2.17	0.07	0.75	1.6	6.5	0.15	1	20.7	6.44	17.94	14.34	35.12	6.04	1.21
fuzzy art	3.14	0.12	1.09	2.1	7.3	0.21	1.01	24.91	7.34	19.03	15.87	36.9	6.87	1.31

Table 3.7 : comparison of different clustering methods for ortho-clustering model using 2 clusters and epsilon=0.001 on estimation of life of converter lining problem (median, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

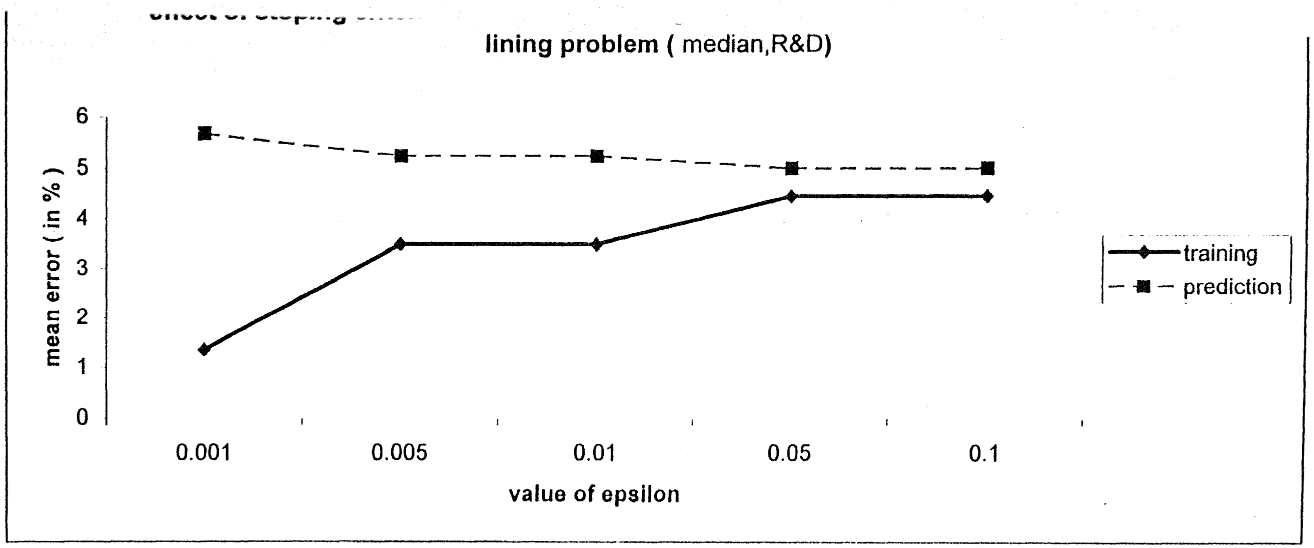

Fig 3.8 : effect of epsilon in ortho-clustering model using fuzzy c-means clustering witth 2 clusters on estimation of life of converter lining problem (median, R&D)

	training statistics							prediction statistics						
epsilon value	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
0.001	1.36	0.03	0.5	1.19	3.68	0.04	1	5.67	0.53	5.15	4.57	10.24	1.09	1.06
0.005	3.48	0.21	1.27	2.98	10.63	0.07	1	5.23	0.4	4.5	3.62	8.85	1.61	1.04
0.01	3.48	0.21	1.27	2.98	10.63	0.07	1	5.23	0.4	4.5	3.62	8.85	1.61	1.04
0.05	4.44	0.31	1.55	3.41	10.84	0.1	1	4.99	0.41	4.54	4.03	9.02	0.97	1.05
0.1	4.44	0.31	1.55	3.41	10.84	0.1	1	4.99	0.41	4.54	4.03	9.02	0.97	1.05

Table 3.8 : effect of epsilon in ortho-clustering model using fuzzy c-means clustering witth 2 clusters on estimation of life of converter lining problem (median, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

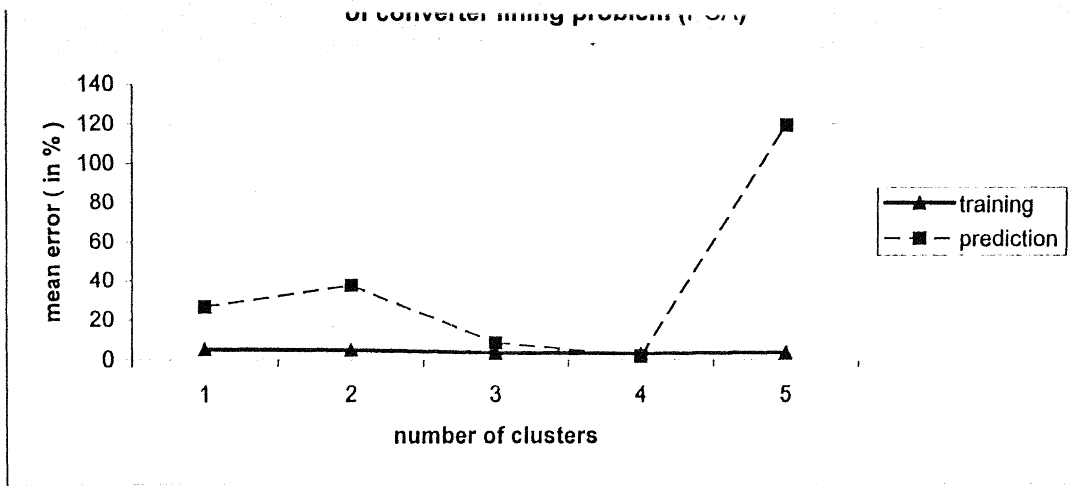

Fig 3.9 : effect of no. of clusters for ortho-clustering model using fuzzy c-means and epsilon=0.005 on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
no. of clusters	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
1	5.29	0.44	1.85	4.04	15.75	0.38	1	26.69	13.56	26.04	25.37	52.06	1.32	1.27
2	4.8	0.39	1.73	3.96	15.98	0.44	1	37.62	27.6	37.15	36.68	74.3	0.94	1.38
3	3.36	0.25	1.38	3.66	12.7	0	1	8.29	0.7	5.9	0.91	9.2	7.38	1.01
4	2.8	0.13	1	2.25	8.1	0.17	1	1.75	0.06	1.67	1.58	3.33	0.17	1.02
5	3.4	0.17	1.15	2.35	9.36	0	1	118.72	165.61	91	49.67	168.39	69.05	0.5

Table 3.9 : effect of no. of clusters for ortho-clustering model using fuzzy c-means and epsilon=0.005 on estimation of life of converter lining problem (PCA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the element corresponding to the best performance

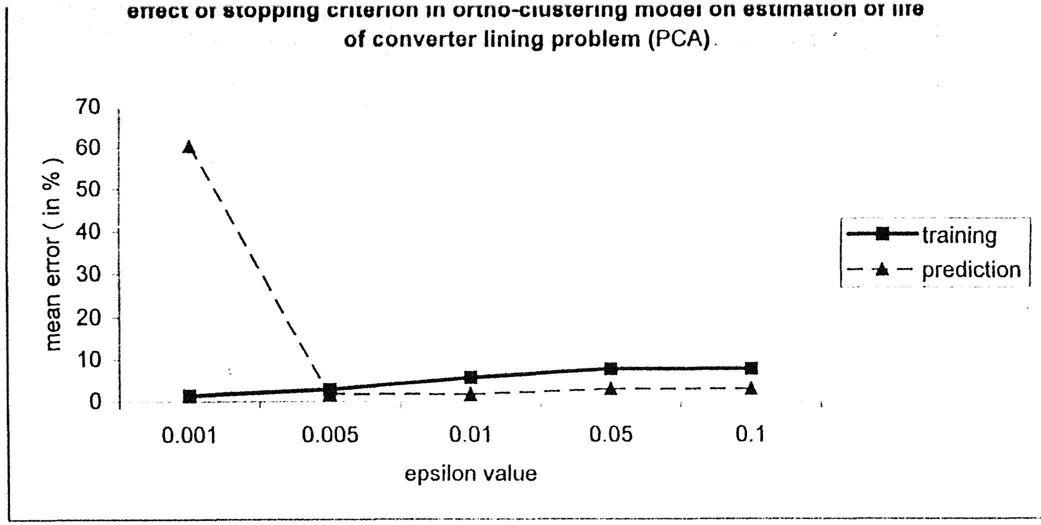

Fig 3.10 : effect of stopping criterion for ortho-clustering using fuzzy c-means clustering with 4 clusters on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
epsilon value	mn error	ms error	rms erro	error std	max error	min erro	slope	mn error	ms error	rms erro	error std	max erro	min error	slope
0.001	1.3	0.03	0.47	1.07	4.17	0.13	1	60.3	68.29	58.43	56.51	116.8	3.79	1.6
0.005	2.8	0.13	1	2.25	8.1	0.17	1	1.75	0.06	1.67	1.58	3.33	0.17	1.02
0.01	5.59	0.55	2.05	4.85	16.49	1.1	1	1.65	0.05	1.55	1.45	3.1	0.21	0.98
0.05	7.68	0.93	2.67	5.81	20.81	1.1	1.01	2.84	0.14	2.69	2.52	5.36	0.32	1.03
0.1	7.68	0.93	2.67	5.81	20.81	1.1	1.01	2.84	0.14	2.69	2.52	5.36	0.32	1.03

Table 3.10 : effect of stopping criterion for ortho-clustering using fuzzy c-means clustering with 4 clusters on estimation of life of converter lining problem (PCA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the element corresponding to the best performance

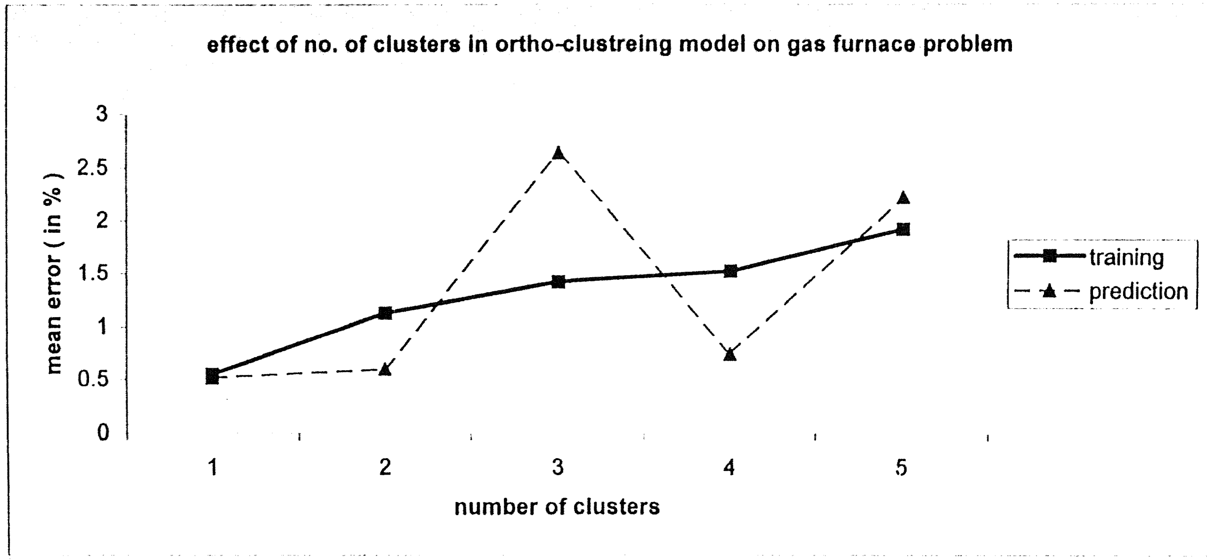

Fig 3.11 : effect of no. of clusters in ortho-clustering model using fuzzy c-means clustering and epsilon=0.001 on modeling of Box Jenkins' gas furnace problem

	trainining statistics								prediction statistics						
no. of clusters	mn error	ms error	rms error	error std	max error	min error	slope		mn error	ms error	rms error	error std	max error	min error	slope
1	0.55	0.01	0.04	0.49	3.04	0	1		0.52	0	0.39	0.19	0.71	0.33	1
2	1.13	0.02	0.08	0.83	4.1	0	1		0.6	0	0.42	0.05	0.65	0.55	1
3	1.42	0.04	0.11	1.33	9.14	0.02	1		2.64	0.07	1.9	0.5	3.14	2.14	0.97
4	1.52	0.05	0.13	1.63	11.67	0	1		0.74	0.01	0.72	0.69	1.43	0.05	1.01
5	1.92	0.07	0.15	1.7	11.73	0.02	1		2.22	0.05	1.6	0.41	2.64	1.81	0.98

Table 3.11 : effect of no. of clusters in ortho-clustering model using fuzzy c-means clustering and epsilon=0.001 on modeling of Box Jenkins' gas furnace problem

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

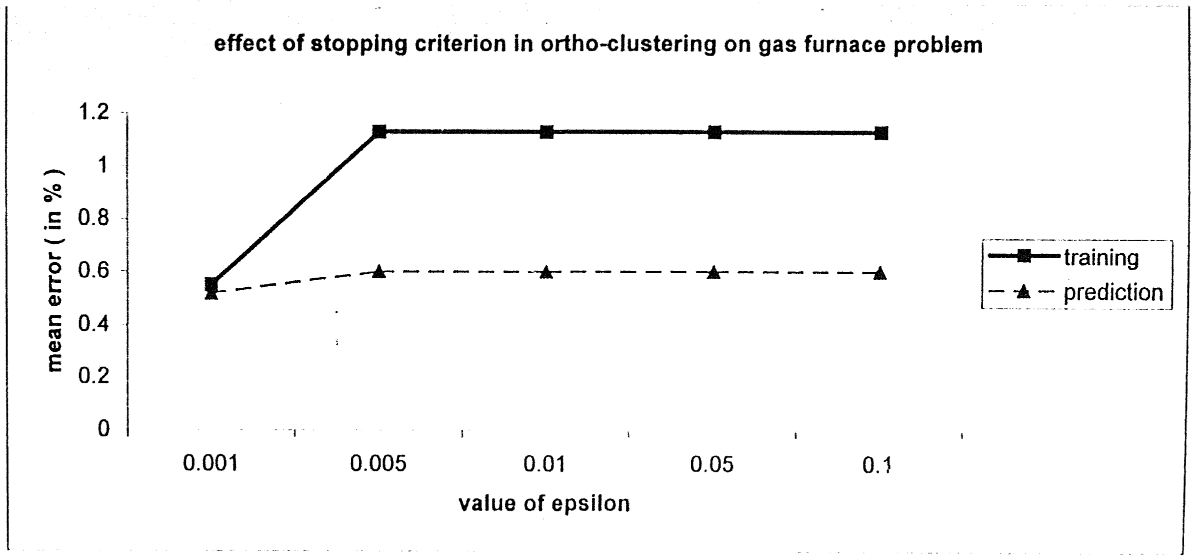

Fig 3.12 : effect of stopping criterion for ortho-clustering model using fuzzy c-mean clustering with 1 cluster on modeling of Box Jenkins' gas furnace problem

	training statistics							prediction statistics						
epsilon value	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
0.001	0.55	0.01	0.04	0.49	3.04	0	1	0.52	0	0.39	0.19	0.71	0.33	1
0.005	1.13	0.02	0.08	0.83	4.06	0.02	1	0.6	0	0.43	0.12	0.72	0.47	1
0.01	1.13	0.02	0.08	0.83	4.06	0.02	1	0.6	0	0.43	0.12	0.72	0.47	1
0.05	1.13	0.02	0.08	0.83	4.06	0.02	1	0.6	0	0.43	0.12	0.72	0.47	1
0.1	1.13	0.02	0.08	0.83	4.06	0.02	1	0.6	0	0.43	0.12	0.72	0.47	1

Table 3.12 : effect of stopping criterion for ortho-clustering model using fuzzy c-mean clustering with 1 cluster on modeling of Box Jenkins' gas furnace problem

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

shaded row represents the best performance

has similar performance, ART and Fuzzy ART has the same performance but som has got the worst performance. The effect of stopping criterion is also different as one can observe from Fig 3.6 and Table 3.6. The training error as epsilon value increases but the prediction is good with epsilon 0.005.

Iii. Results of estimation of converter lining problem (median, R&D)

From the results given in Table B, it can be observed that Fuzzy C-means clustering shows good performance with two clusters and keeping epsilon to be 0.001, the training error is 1.36 and prediction error is 5.67. SOM shows the worst performance with training error 3.5 and prediction error 34.7. From the Fig 3.7 and Table 3.7 it can be deduced that the division of data into two clusters gives good performance, increasing the number of clusters beyond two results in worse performance. The effect of stopping criterion can be observed from Fig 3.8 and Table 3.8. The training error decreases as epsilon value increases but the prediction is good with epsilon 0.001.

iv. Results of estimation of converter lining problem (PCA)

From the results given in Table D, it can be observed that the best performance is given by fuzzy c-means clustering with epsilon value equal to 0.005, the data are divided into 4 clusters, the training error is 2.8 and the prediction error is 1.75. The effect of division of data into different clusters has changed for this problem. From the Fig 3.9 and Table 3.9 it can be deduced that the division of data into four clusters has a better performance for prediction i.e. 2.8, 1.75. From Fig. 3.10 and Table 3.10, it can be observed that with epsilon error there is over fitting of the model which caused the prediction to be worst. The model with epsilon value equal to 0.005 has better performance.

3.2.2.5 Results of modeling of Box Jenkins' gas furnace problem

From the results given in Table E, it can be observed that the best performance is given by fuzzy c-means clustering with epsilon value equal to 0.001, the data are divided into 1 cluster, the training error is 0.55 and the prediction error is 0.52. The effect number of clusters is shown in the Fig 3.11 and Table 3.11 and the effect of stopping criterion can be observed in Fig 3.12 and Table 3.12.

3.3. Conclusions

This work brings out a comparison of the performance of various clustering algorithms and also looks at the effect of stopping criterion, epsilon in determining the significant terms of the model. Among the clustering methods used, K-means shows a better performance. Division of data into two clusters gives better results. From the results of all the

problems one can deduced that by increasing the epsilon value the training gets poorer, but the prediction shows an inconsistent behavior. In the case of PCA problem the prediction is good with epsilon value 0.005 but for all the problems the results are good with epsilon value 0.001. Also one can observe that by increasing the number of clusters the training gets better but the prediction is good with two clusters for estimation of life of converter lining problem. In Box problem the results are good with single cluster, as the data has less complexity embedded in it.

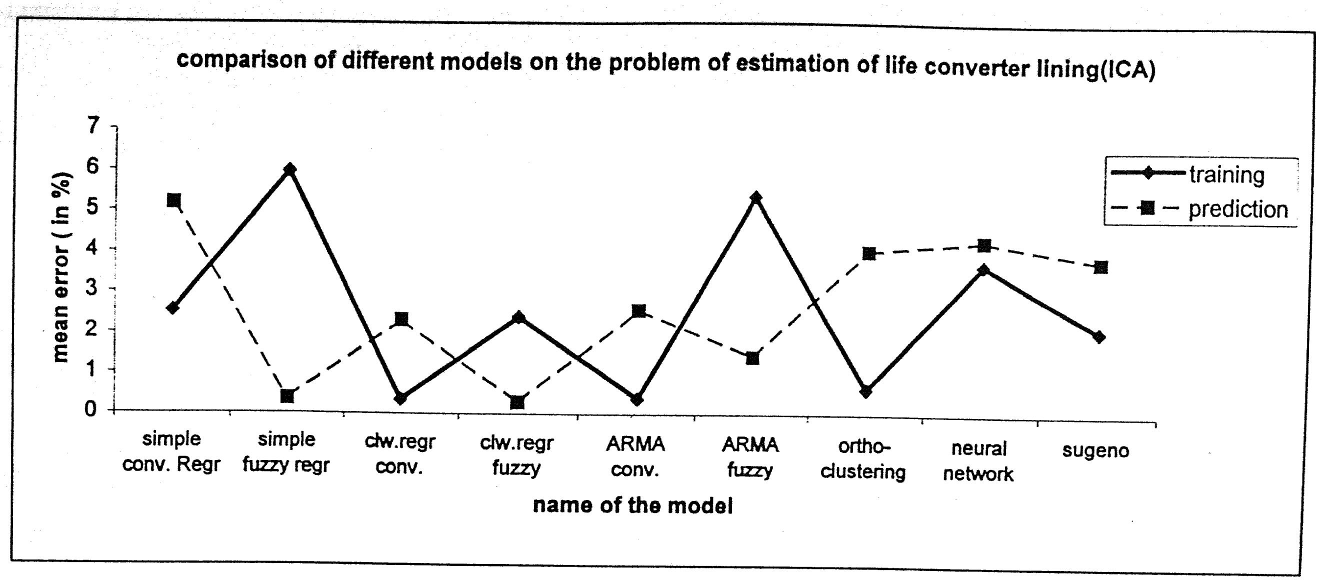

Fig. 4.1 comparison of different models on estimation of life of converter lining problem (ICA)

e of the model	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ple regr conv.	2.53	0.14	1.03	2.73	8.72	0.1	1	5.18	0.28	3.72	0.95	6.13	4.23	0.99
ple regr fuzzy	5.97	0.65	2.23	5.4	19.58	0.61	1.04	0.36	0	0.3	0.23	0.59	0.14	1
v.regr conv.	0.35	0	0.15	0.42	1.57	0.06	1	2.32	0.06	1.68	0.5	2.82	1.82	1.02
v.regr fuzzy	2.4	0.06	0.68	0.51	3.09	1.25	0.98	0.29	0	0.24	0.19	0.48	0.09	1
RMA conv.	0.39	0	0.13	0.24	1.02	0.02	1	2.58	0.1	2.27	1.91	4.5	0.67	1.02
RMA fuzzy	5.37	0.41	1.84	3.42	13.15	1.41	1.02	1.43	0.03	1.19	0.9	2.33	0.53	1.01
io-clustering	0.64	0.01	0.27	0.74	2.47	0	1	4.04	0.28	3.77	3.48	7.53	0.56	0.97
sugeno	2.1		3.4		4.9	0.21	1.01	3.8		3.1		3.12	0.6	0.99
ıral network	3.2		4.82		10.85	0.214	1.024	4.37		4.399		4.851	3.89	0.997

Table 4.1 comparison of different models on estimation of life of converter lining problem (ICA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimur clw.regr =cluster wise regression, regr = regress conv. = conventional
shaded row represents the element corresponding to the best performance

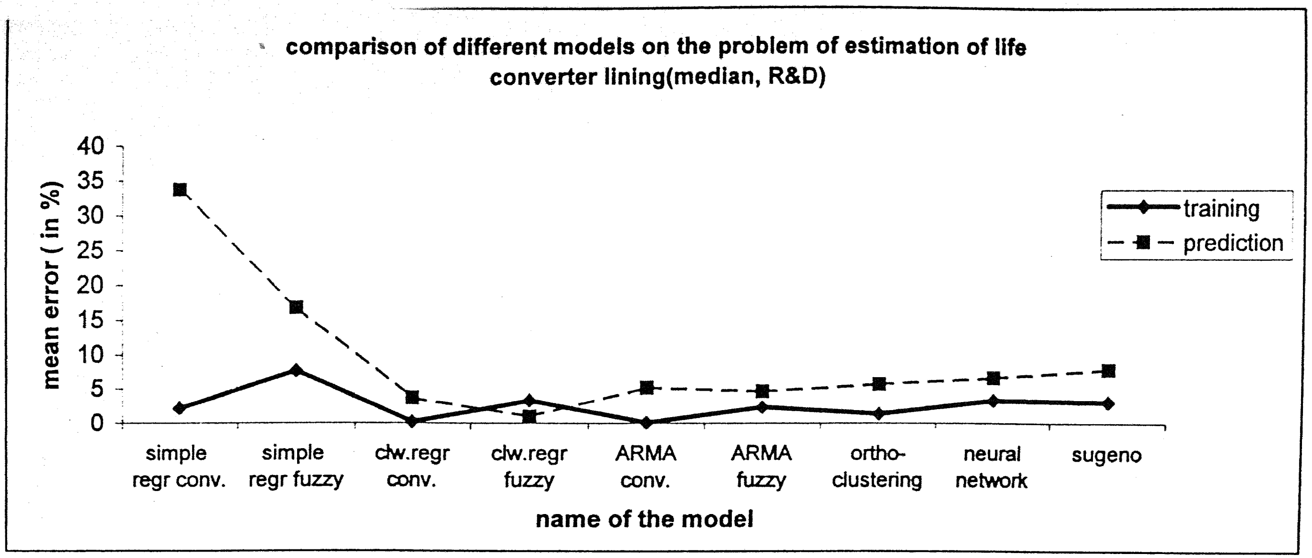

Fig. 4.2 comparison of different models on estimation of life of converter lining problem (median, R&D)

	training statistics							prediction statistics						
e of the model	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ple regr conv.	2.19	0.07	0.73	1.47	4.99	0.23	1	33.65	18.96	30.79	27.63	61.28	6.03	1.34
ple regr fuzzy	7.61	0.9	2.62	5.62	19.24	0.72	1.03	16.78	2.84	11.91	1.43	18.21	15.35	1.01
v.regr conv.	0.2	0	0.08	0.19	0.61	0.01	1	3.7	0.24	3.47	3.23	6.93	0.47	1.03
v.regr fuzzy	3.29	0.18	1.19	2.75	10.25	0.26	1.02	1.04	0.02	0.89	0.72	1.76	0.32	1.01
RMA conv.	0.1	0	0.03	0.07	0.24	0.02	1	5.22	0.39	4.43	3.47	8.68	1.75	1.03
RMA fuzzy	2.35	0.06	0.7	0.55	3.47	1.26	0.98	4.62	0.22	3.34	0.96	5.58	3.65	1.01
no-clustering	1.36	0.03	0.5	1.19	3.68	0.04	1	5.67	0.53	5.15	4.57	10.24	1.09	1.06
sugeno	3.1		3.78		7.8	0.11	0.99	7.8		9.1		13.1	0.89	1.08
ural network	3.29		3.97		8.27	0.16	0.99	6.59		8.67		12.2	1	1.07

Table 4.2 comparison of different models on estimation of life of converter lining problem (median, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimur clw.regr =cluster wise regression, regr = regress conv. = conventional

shaded row represents the element corresponding to the best performance

Chapter 4

4.1 Results and discussion

In the present section the performance of all the models is evaluated by selecting the best results presented in the previous chapters.

4.2.1 Results of estimation of life converter lining problem (ICA)

From the Table 4.1 and Fig 4.1 it can be observed that cluster wise regression with fuzzy model shows best performance, the training error is 2.4 and the prediction error is 0.29. But the conventional regression gives the worst results with training error 2.53 and prediction error 5.18. From the Table 4.1 and Fig 4.1 it can be deduced that in all the methods the fuzzified model has better performance when compared to the conventional one. In simple regression the conventional model has a training error of 2.53 and prediction error of 5.18.

4.2.2 Results of estimation of life converter lining problem (median, R&D)

From the results given in Fig 4.2 and Table 4.2 it can be observed that the division of data into different clusters has a predominant effect upon the performance of the model. In simple conventional regression, the training and prediction errors are 2.19 and 33.665 where as in the cluster wise conventional regression, the training and prediction errors are 0.2 and 3.7 respectively. Also it can be seen that the ARMA method is able to estimate better than the simple regression. The conventional ARMA has the training error of 0.1 and prediction error of 5.22 which is quite low when compared to the simple conventional regression. The effect of fuzzyfication is very low for this problem, as it can be observed that the training and prediction errors of fuzzy cluster wise regression (3.29 and 1.04 respectively) are not better than the those of conventional one.

4.2.3 Results of estimation of life converter lining problem (mean, R&D)

The results are given in Table 4.3. From Fig.4.3. and Table 4.3. it can be seen that the fuzzyfication has much better prediction though the training is poorer, i.e. the conventional cluster wise has a training error of 0.21 and prediction error of 3.1 where as cluster wise fuzzy regression has a training error of 2.42 and a prediction error of 1.2. In this

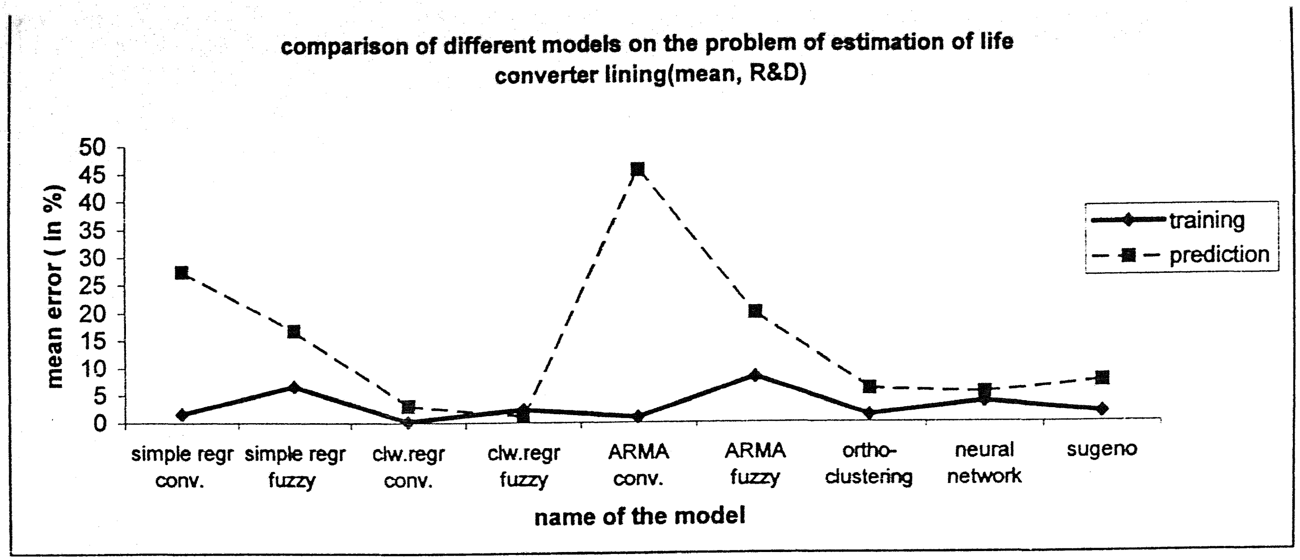

Fig. 4.3 comparison of different models on estimation of life of converter lining problem (mean, R&D)

	training statistics							prediction statistics						
me of the model	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
mple regr conv.	1.6	0.04	0.58	1.35	4.67	0.07	1	27.42	10.07	22.44	15.99	43.4	11.43	1.16
mple regr fuzzy	6.65	0.73	2.36	5.34	18.7	0.45	1.02	16.79	3.33	12.91	7.18	23.97	9.61	1.17
clw.regr conv.	0.21	0	0.08	0.19	0.65	0.03	1	3.1	0.13	2.59	1.94	5.04	1.15	1.03
clw.regr fuzzy	2.42	0.06	0.68	0.31	2.95	2.02	0.98	1.2	0.02	1.11	1.02	2.21	0.18	1.01
ARMA conv.	0.95	0.01	0.32	0.58	2.19	0.22	1	45.63	25.74	35.88	22.2	67.82	23.43	0.54
ARMA fuzzy	8.24	1.06	2.98	6.21	20.06	0.3	1.01	19.93	4.51	15.02	7.35	27.28	12.58	0.93
sugeno	1.8		0.68		6.7	0.03	1	7.48		6.45		9.23	2.1	0.93
rtho-clustering	1.29	0.04	0.57	1.61	5.3	0.01	1	6.08	0.45	4.72	2.74	8.82	3.34	0.94
neural network	3.72		4.59		9.4	0.682	0.98	7.16		8.98		12.58	1.75	1.07

Table 4.3 comparison of different models on estimation of life of converter lining problem (mean, R&D)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimur clw.regr =cluster wise regression, regr = regres: conv. = conventional

shaded row represents the element corresponding to the best performance

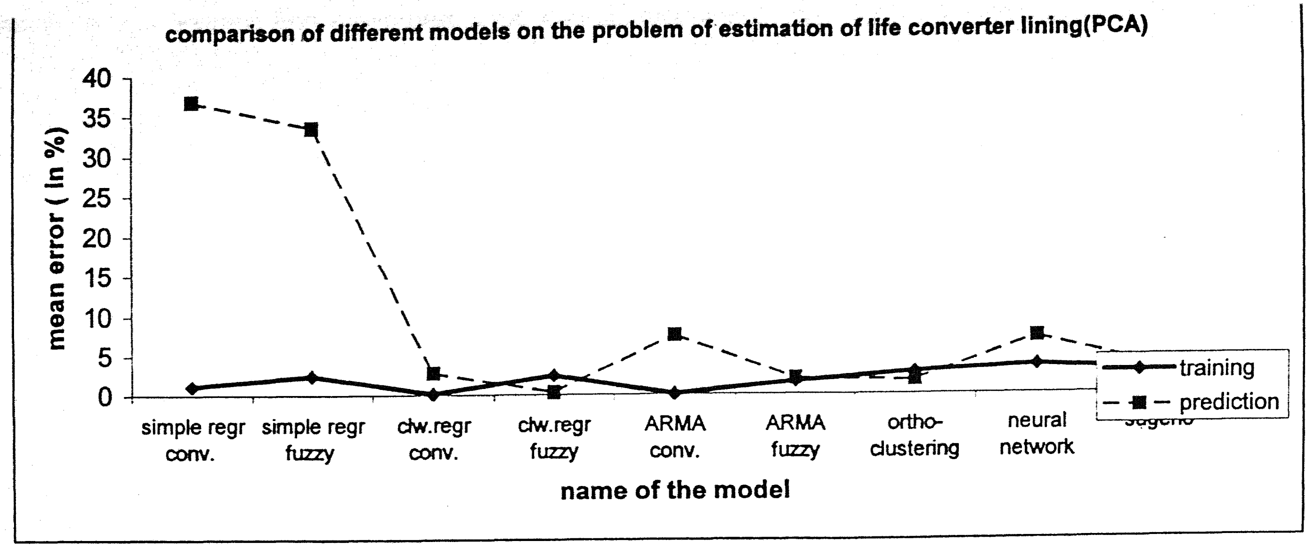

Fig. 4.4 comparison of different models on estimation of life of converter lining problem (PCA)

	training statistics							prediction statistics						
me of the model	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
mple regr conv.	1.08	0.02	0.37	0.8	3.17	0.1	1	36.85	13.59	26.07	0.98	37.84	35.87	1.37
imple regr fuzzy	2.43	0.07	0.74	1.1	4.12	0.7	0.98	33.57	11.28	23.75	0.96	34.53	32.61	1.34
clw.regr conv.	0.11	0	0.04	0.07	0.24	0.02	1	2.78	0.08	1.98	0.34	3.12	2.44	1.03
clw.regr fuzzy	2.4	0.06	0.67	0.13	2.62	2.16	0.98	0.33	0	0.32	0.31	0.65	0.02	1
ARMA conv.	0.05	0	0.02	0.03	0.11	0.01	1	7.48	0.62	5.55	2.38	9.86	5.1	1.02
ARMA fuzzy	1.6	0.03	0.5	0.61	2.41	0.8	1.02	2	0.04	1.42	0.12	2.12	1.89	1
sugeno	2.9		2.1		5.23	1.2	1.01	3.32		4.4		6.32	0.85	1.01
ortho-clustering	2.8	0.13	1	2.25	8.1	0.17	1	1.75	0.06	1.67	1.58	3.33	0.17	1.02
neural network	3.56		3.948		6.34	0.19	0.97	7.16		8.98		12.58	1.75	1.07

Table 4.4 comparison of different models on estimation of life of converter lining problem (PCA)

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error,
max error = maximum error, min error = minimur clw.regr =cluster wise regression, regr = regress conv. = conventional
shaded row represents the element corresponding to the best performance

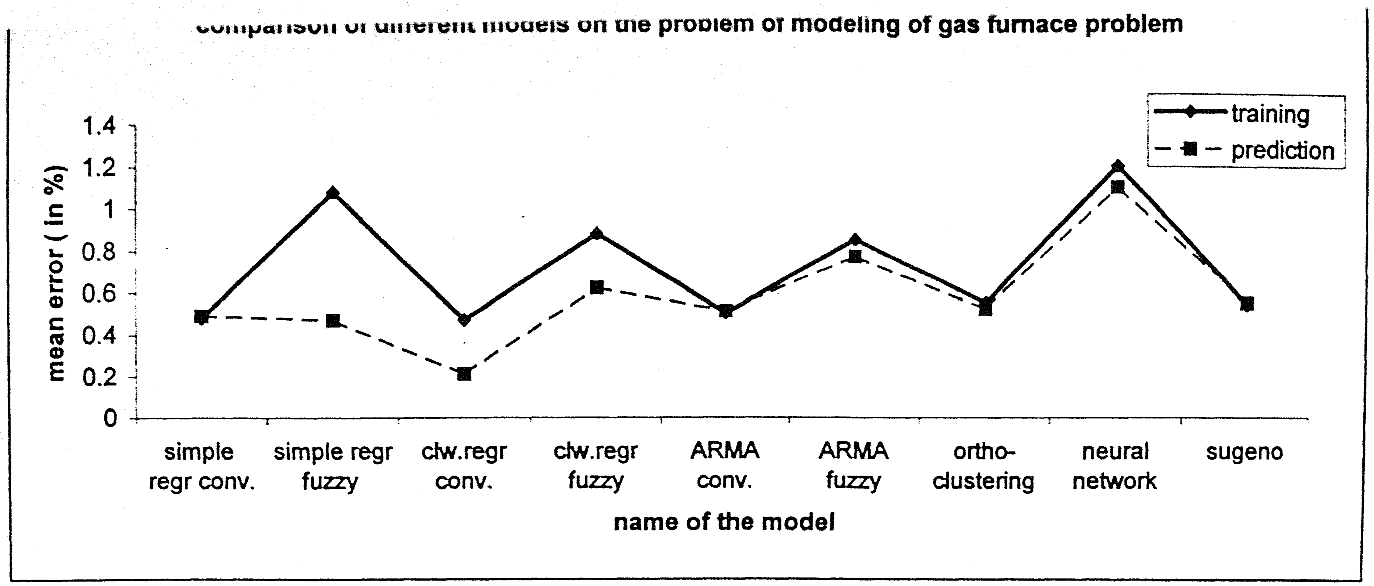

Fig. 4.5 comparison of different models on modeling of Box Jenkins' gas furnace problem

	training statistics							prediction statistics						
of the model	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
le regr conv.	0.48	0	0.04	0.47	3.87	0	1	0.49	0	0.41	0.32	0.8	0.17	1
le regr fuzzy	1.08	0.02	0.07	0.67	3.55	0.01	0.99	0.47	0	0.4	0.32	0.79	0.15	1
v.regr conv.	0.47	0	0.04	0.45	3.84	0	1	0.21	0	0.18	0.16	0.36	0.05	1
v.regr fuzzy	0.88	0.01	0.06	0.53	3.15	0	0.99	0.62	0	0.46	0.21	0.83	0.41	0.99
RMA conv.	0.5	0	0.04	0.4	2.96	0	1	0.51	0	0.36	0.01	0.52	0.49	1
RMA fuzzy	0.85	0.01	0.06	0.55	3.73	0	0.99	0.77	0.01	0.65	0.5	1.28	0.27	0.99
sugeno	0.54		0.04	0.48	3.01		0.99	0.55		0.41	0.21	0.78	0.32	1
o-clustering	0.55	0.01	0.04	0.49	3.04	0	1	0.52	0	0.39	0.19	0.71	0.33	1
ral network	1.2	0.01	0.27	0.74	2.47	0	1	1.1	0.28	3.77	3.48	7.53	0.56	0.97

Table 4.5 comparison of different models on modeling of Box Jenkinson's gas furnace problem

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimur clw.regr =cluster wise regression, regr = regress conv. = conventional

shaded row represents the element corresponding to the best performance

problem ARMA method of modeling shows worst performance with a training error of 0.95 and prediction error of 45.63.

4.2.4 Results of estimation of life converter lining problem (PCA)

From the results given in Table 4.4 and Fig. 4.4 it can be deduced that the fuzzyfication has much effect upon the performance of the model. The training and prediction errors of conventional cluster wise regression are 0.11 and 2.78 where as the fuzzy cluster wise regression training and prediction errors are 2.4 and 0.33. In this case also the division of data shows better performance than the simple regression and ARMA. The training and prediction errors of conventional regression are 1.08 and 36.85 respectively where as the training and prediction errors of conventional cluster wise regression are 0.11 and 2.78. ARMA method of modeling shows much better performa- nce than the simple regression. The fuzzyfied ARMA has a training error of 1.6 and prediction error of 2.00 where as the fuzzy simple regression has a training error of 2.43 and prediction error of 33.57.

4.2.5 Results of modeling of Box Jenkins' gas furnace problem

The results are given Table 4.5 and a comparison is shown in the Fig 4.5. From the results it can be deduced that the fuzzyfication of data does not yield good results. The training and prediction errors of simple conventional regression are 0.48 and 0.49 respectively. But for the fuzzy simple regression the training and prediction errors are 1.08 and 0.47 respectively. The division of data yields good results for conventional regression but for the fuzzyfied data the clustering makes the performance worse. The training and prediction errors of cluster wise conventional regression are 0.47 and 0.21 where as for the simple conventional regression are 0.48 and 0.49 . The training and prediction errors of cluster wise fuzzy regression are 0.88 and 0.62 where as for simple fuzzy regression these are 1.08 and 0.47.

Chapter 5

1 General conclusions

This work mainly emphasizes on comparing the performances of different modelg techniques . A new approach to fuzzy least square method is proposed for multi input stem. The effect of modeling functions upon the performance of the model is studied. ızzified models of ARMA and cluster wise regression are developed by applying the ızzified least square regression to their conventional models. The effect of different clusring methods on the performance of orthogonal parameter estimator and cluster wise gression model is evaluated.

From the results of the example problems it can be concluded that the fuzzificaon of the data decreases t he precision. For the fuzzified model the prediction is better ıan the conventional models though the training poorer. The division of data results in etterment of the modeling. ARMA proves to be much better modeling technique to the imple least square regression. Fuzzification of the ARMA yields in better prediction ompared to the conventional ARMA for the system having inherent imprecision. For the imple system like Box Jenkins' gas furnace modeling the fuzzification does not yields ood results. From results of orthogonal clustering it can be concluded that the k-means lustering is more efficient in dividing the input space.

.2 Scope for future

1. The method of implementation for simple fuzzy regression with fuzzified input variables and fuzzy model parameters has to be studied.
2. Effect of scaling of the data on the performance of the modeling function has to be evaluated.
3. Effect of different fuzzification and defuzzification methods on the performance of the model has to be evaluated.
4. An information criterion has to be developed for determining the optimum number of clusters for better classification of the data.
5. Feasibility of extending the existing information criterion such as AIC and BIC [16] for determining the optimum order in conventional ARMA, to fuzzy ARMA has to be evaluated.

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Appendix

A.1 L_R FUZZY REAL NUMBERS

Fuzzy Real Numbers

Let R be the set of real numbers and $n \in R$ a given real number. Form the real number n one can construct a fuzzy real number N as a fuzzy set that covers number n. When the fuzziness of N is removed it reduces exactly to n[2 blue].

Definition A.1 : N is a fuzzy real number if and only if: (i) it is a fuzzy subset of the set R of real numbers, (ii) its membership function $\mu_N(x)$ has the following properties

a. $\mu_N(x)$ is a continuous function
b. $\forall x \in (-\infty, c]$, $\mu_N(x)=0$
c. $\mu_N(x)$ is strictly increasing in $[c,a]$
d. $\forall x \in [a,b]$, $\mu_N(x)=1$
e. $\mu_N(x)$ is strictly decreasing in $[b,d]$
f. $\forall x \in [d,+\infty)$, $\mu_N(x)=0$

Let y(x) be a real function $y(x):R \rightarrow [0,1]$ that prossesses the properties of $\mu_N(x)$ of definition A.1, and can be considered the membership funciton of a fuzzy real number.

Definition A.2: Let L(x) and R(x) be two funcitons satisfying the conditions of Def. A.1 Then as L_R fuzzy number M around the classical number m, is defined a fuzzy number M with membership function:

$$\mu_M(x)= \begin{cases} L((m-x)/\alpha), x<=m \\ R((x-m)/\beta), x>=m \end{cases}$$

Where m is the modal value and α,β are spread parameters. Since the L_R fuzzy number is fully determined by the triad of parameters m,α and β it is symbolised by: $M=(m,\alpha,\beta)$.

Theorem A.1

Let two L_R fuzzy numbers $M=(m,\alpha,\beta)$ and $N=(n,\gamma,\delta)$. Then one can show [2] the following:

1. Fuzzy addition

$$M+N=(m,\alpha,\beta)+(m,\gamma,\delta)=(m+n,\alpha+\gamma,\beta+\delta)$$

2. Fuzzy opposite

$-M= -(m,\alpha,\beta)=(-m,\alpha,\beta)$ R-L numbers

3. Fuzzy subtraction

The subtraction has sense only between L-R and R-L, L-L and L-L,R-R and R-R numbers (not between R-L and R-L numbers)

$$M-N = M+(-N)$$

4. Fuzzy inverse

$1/m= (1/m,\beta/m^2,\alpha/m^2)$ R- number

5. Fuzzy multiplication

Three cases are distinguished:

Case A: If m>0 and n>0, then

$$MN=(m,\alpha,\beta)(n,\gamma,\delta)=(mn,n\alpha-m\delta,n\beta-m\gamma)= -[(-(m,\alpha,\beta))(n,\gamma,\delta)]$$

Case B: If m<0 and n>0, then

$$MN=(m,\alpha,\beta)(n,\gamma,\delta)=(mn,m\gamma+m\alpha,m\delta+m\beta)$$

Case C: If m<0 and n<0, then

$$MN=(m,\alpha,\beta)(n,\gamma,\delta)=(mn,-n\beta-m\delta,-n\alpha-m\gamma) = -[(-(m,\alpha,\beta))(-(n,\gamma,\delta))]$$

6. Fuzzy division

$$M/N=M.(1/N)=(m,\alpha,\beta)(n,\gamma,\delta)+(mn,(m\delta+n\alpha)/n^2,(m\gamma+n\beta)/n^2)$$

A.2 Method of Fuzzification

The method of fuzzification used in the present work is a simple method where the standard deviation of all the samples for each variable is used as the spread of the fuzzy number of that corresponding variable. The spread can be multiplied by any numeric constant in order to weigh the spread. The fuzzified number of any variable *x* is given as $\tilde{X} = (x,\alpha\sigma,\beta\sigma)$ where α and β are constants, σ is the standard deviation of *x* in observed samples.

A.3 Method of Defuzzification

the crisp value of a fuzzy number is evaluated by defuzzifying the corresponding fuzzy number with a suitable defuzzification technique. The present work applies the standard center of gravity method to defuzzify the fuzzy number.

no	HM temp.	Blow O2	tap-tap time	Lime	ore	Bath C			Basicity	%FeO	%MgO	%CaO	%MnO	of heats
1\10	1274.03	6513.96	102.251	9.63338	2.52558	0.090532	0.040618	0.046787	3.10974	20.1074	5.27128	48.3341	2.36154	772
1\11	1280.72	6467.77	99.7523	10.3934	3.00652	0.083028	0.039801	0.04761	2.95135	20.3338	5.12946	47.3065	1.82676	560
1\2	1268.12	6980.12	140.695	16.4524	1.42934	0.14872	0.052358	0.036517	2.63659	17.7688	3.74188	49.0289	3.01225	563
1\3	1252.12	7002.61	175.15	14.2833	1.15569	0.073785	0.042796	0.02564	2.47568	19.8751	3.40674	47.2282	2.94684	499
1\4	1232.97	6857.39	137.666	15.7592	1.5019	0.069777	0.048577	0.03707	2.49685	18.4437	3.05467	49.4806	1.84867	937
1\5	1228.11	7043.94	117.581	14.2333	2.12	0.089298	0.04296	0.033175	2.73586	20.4845	4.43195	48.6253	1.43083	595
1\6	1235.48	6964.83	134.779	13.0952	3.10135	0.079736	0.033374	0.04	2.50831	20.4511	5.31683	47.0311	1.07206	539
1\7	1247.9	6967	128.557	11.4379	2.25253	0.088591	0.037864	0.036909	2.6167	19.5651	4.79124	48.7944	1.35381	532
1\8	1259.56	6493.27	104.521	10.6612	1.82296	0.095519	0.036245	0.043714	2.67862	17.1683	4.84844	50.1312	2.16963	662
2\10	1278.53	6767.83	97.8564	10.7047	2.77052	0.076412	0.039485	0.045711	2.8035	21.4174	4.21158	47.21	1.50842	607
2\6	1242.52	6801.22	133.921	12.1535	2.71821	0.07925	0.034	0.037117	2.56382	18.6164	5.19177	49.2515	1.09374	712
2\7	1262.17	6419.67	116.784	10.4651	1.9778	0.097322	0.038628	0.038793	2.67557	18.6628	5.32563	48.8925	1.34292	724
2\8	1260.12	6319.54	113.064	10.027	1.94443	0.083917	0.03549	0.038336	3.18154	17.6008	5.4675	49.7808	2.705	746
3\4	1234.59	7011.5	140.178	12.6994	2.76217	0.073272	0.034192	0.033967	2.64884	20.7927	5.46568	47.5912	1.14136	546
3\6	1261.02	6519.13	106.516	10.532	1.97692	0.100815	0.038021	0.041075	2.65012	19.2193	5.2324	48.4078	1.55768	652

Table 1.1 data sheet for estimation of life of converter lining problem (ICA)

campaign no	mean hm/(hm+sc	mean Si in hm	mean Mn in hm	mean blow O2	mean Tap. Temp	mean tap-tap tin	mean Lime	mean Ore	mean Bath C	mean S	mean P	mean Basicity	mean %FeO	mean %CaO	Actual of heat
1\10	0.922119	0.880105	0.694967	6513.96	1666.13	102.251	9.63338	2.52558	0.090532	0.040618	0.046787	3.10974	20.1074	48.3341	772
1\11	0.905884	1.0431	0.657711	6467.77	1670.65	99.7523	10.3934	3.00652	0.083028	0.039801	0.04761	2.95135	20.3338	47.3065	560
1\2	0.933459	1.18129	0.597939	6980.12	1671.9	140.695	16.4524	1.42934	0.14872	0.052358	0.036517	2.63659	17.7688	49.0289	563
1\3	0.942544	1.12535	0.580189	7002.61	1661.22	175.15	14.2833	1.15569	0.073785	0.042796	0.02564	2.47568	19.8751	47.2282	499
1\4	0.942501	1.16596	0.635481	6857.39	1661.03	137.666	15.7592	1.5019	0.069777	0.048577	0.03707	2.49685	18.4437	49.4806	937
1\5	0.908138	1.10912	0.546531	7043.94	1666.74	117.581	14.2333	2.12	0.089298	0.04296	0.033175	2.73586	20.4845	48.6253	595
1\6	0.904731	1.27833	0.707137	6964.83	1680.28	134.779	13.0952	3.10135	0.079736	0.033374	0.04	2.50831	20.4511	47.0311	539
1\7	0.910444	1.04208	0.627623	6967	1677.37	128.557	11.4379	2.25253	0.088591	0.037864	0.036909	2.6167	19.5651	48.7944	532
1\8	0.910769	0.924724	0.694303	6493.27	1679.42	104.521	10.6612	1.82296	0.095519	0.036245	0.043714	2.67862	17.1683	50.1312	662
2\10	0.90487	1.11022	0.550334	6767.83	1663.84	97.8564	10.7047	2.77052	0.076412	0.039485	0.045711	2.8035	21.4174	47.21	607
2\6	0.902376	1.14695	0.666119	6801.22	1673.24	133.921	12.1535	2.71821	0.07925	0.034	0.037117	2.56382	18.6164	49.2515	712
2\7	0.90675	0.932009	0.667626	6419.67	1673.87	116.784	10.4651	1.9778	0.097322	0.038628	0.038793	2.67557	18.6628	48.8925	724
2\8	0.904433	0.952568	0.717364	6319.54	1675.33	113.064	10.027	1.94443	0.083917	0.03549	0.038336	3.18154	17.6008	49.7808	746
3\4	0.910845	1.29996	0.699404	7011.5	1667.3	140.178	12.6994	2.76217	0.073272	0.034192	0.033967	2.64884	20.7927	47.5912	546
3\6	0.901154	0.935502	0.664253	6519.13	1668.77	106.516	10.532	1.97692	0.100815	0.038021	0.041075	2.65012	19.2193	48.4078	652

Table 1.2 data sheet for estimation of life of converter lining problem (PCA)

1\10	0.922119	0.880105	10.8924	0.694967	6513.96	14.8489	63.2895	37.0466	9.63338	22.1264	2.5641	28.2051	5.27128	772
1\11	0.905884	1.0431	28.5714	0.657711	6467.77	19.0647	57.1429	44.6429	10.3934	27.49	13.5135	40.5405	5.12946	560
1\2	0.933459	1.18129	67.8363	0.597939	6980.12	24.7312	83.9416	42.984	16.4524	18.9024	40.9091	21.5385	3.74188	563
1\3	0.942544	1.12535	57.5	0.580189	7002.61	14.0496	89.5062	75.5511	14.2833	56.9892	46.3158	35.7895	3.40674	499
1\4	0.942501	1.16596	64.4444	0.635481	6857.39	17.6136	74.0458	45.4642	15.7592	55.1769	53.9326	14.4444	3.05467	937
1\5	0.908243	1.10899	48.0069	0.546706	7043.32	28.8793	72.4786	38.2403	14.2341	32.0683	28.5714	38.3459	4.43195	595
1\6	0.904731	1.27833	67.5522	0.707137	6964.83	30.137	87.8277	31.1688	13.0952	39.2276	48.5915	29.5775	5.31683	539
1\7	0.910444	1.04208	36.9048	0.627623	6967	28.1369	83.6852	46.8045	11.4379	39.7727	40.2062	24.7423	4.79124	532
1\8	0.910769	0.924724	17.7586	0.694303	6493.27	30.0687	66.0377	31.5254	10.6612	33.195	22.0183	5.50459	4.84844	662
2\10	0.90487	1.11022	48.6622	0.550334	6767.83	15.2174	60.6419	41.6804	10.7047	40.6186	20	47.3684	4.21158	607
2\6	0.902376	1.14695	55.7637	0.666119	6801.22	27.8351	78.4173	44.1011	12.1535	40.1667	49.2462	13.6364	5.19177	712
2\7	0.90675	0.932009	13.3903	0.667626	6419.67	26.383	68.8456	38.8122	10.4651	35.0413	24.0418	14.9826	5.32563	724
2\8	0.904433	0.952568	21.1749	0.717364	6319.54	26.4586	72.9252	31.7694	10.027	32.7893	7.69231	8.33333	5.4675	746
3\4	0.910845	1.29996	76.1639	0.699404	7011.5	27.234	86.7675	39.1941	12.6994	49.4888	33.5484	34.1935	5.46568	546
3\6	0.901154	0.935502	14.1066	0.664253	6519.13	21.6749	69.2427	42.0245	10.532	40.0347	28.5156	20.8661	5.2324	652

Table 1.3 data sheet for estimation of life of converter lining problem (mean, R&D)

campaign no	median hm/(hm+sc	median %Si	median %Mn	median Blow O2	median Tap temp.	median tap-tap tin	median Lime add.	median bath C	median slag basic	median FeO	median MgO	Actual no. of heats
1\10	0.892086	0.88	0.7	6528	1668	80	9.7	0.07	3.11	19.6	5.24	772
1\11	0.889706	1	0.64	6504	1675.5	75	10.2	0.07	3	20.29	4.97	560
1\2	0.925009	1.19	0.58	6973	1672	101	16.6	0.09	2.59	17.41	3.71	563
1\3	0.926036	1.115	0.55	6970	1658	122.5	14.7	0.05	2.54	19.85	3.39	499
1\4	0.927007	1.26	0.52	6841	1663	92	15.9	0.05	2.49	18.075	3.1	937
1\5	0.889706	1.08	0.54	7080	1670	88	14.3	0.07	2.75	20.5	4.34	595
1\6	0.889706	1.27	0.68	6995	1684	103	13.35	0.06	2.53	19.28	5.31	539
1\7	0.889706	1	0.63	6959	1682	100	11.5	0.06	2.58	18.59	4.78	532
1\8	0.885496	0.91	0.68	6491	1684	82	10.5	0.07	2.66	17.04	4.77	662
2\10	0.891304	1.085	0.53	6818	1669	77	10.4	0.06	2.91	20.48	4.22	607
2\6	0.883721	1.14	0.67	6798	1679	100	12.1	0.06	2.51	18.175	5.205	712
2\7	0.886364	0.91	0.66	6476	1674	87	10.4	0.07	2.71	18.31	5.26	724
2\8	0.884615	0.91	0.72	6379.5	1676	89	10.1	0.06	2.69	17.83	5.425	746
3\4	0.891304	1.28	0.7	7048	1674	105	12.6	0.06	2.67	20.5	5.38	546
3\6	0.884615	0.92	0.67	6577	1665	84	10.5	0.06	2.65	19.36	5.165	652

Table 1.4 data sheet for estimation of life of converter lining problem (median, R&D)

gas flow rate	CO2 conc.
-0.109	53.8
0	53.6
0.178	53.5
0.339	53.5
0.373	53.4
0.441	53.1
0.461	52.7
0.348	52.4
0.127	52.2
-0.18	52
-0.588	52
-1.055	52.4
-1.421	53
-1.52	54
-1.302	54.9
-0.814	56
-0.475	56.8
-0.193	56.8
0.088	56.4
0.435	55.7
0.771	55
0.866	54.3
0.875	53.2
0.891	52.3
0.987	51.6
1.263	51.2
1.775	50.8
1.976	50.5
1.934	50
1.866	49.2
1.832	48.4
1.767	47.9
1.608	47.6
1.265	47.5
0.79	47.5
0.36	47.6
0.115	48.1
0.088	49
0.331	50
0.645	51.1
0.96	51.8
1.409	51.9
2.67	51.7
2.834	51.2
2.812	50
2.483	48.3
1.929	47
1.485	45.8
1.214	45.6
1.239	46
1.608	46.9
1.905	47.8
2.023	48.2
1.815	48.3

Table 1.5: Box data

gas flow rate	CO2 conc.
0.536	47.9
0.122	47.2
*	*
0.164	48.1
0.671	49.4
1.019	50.6
1.146	51.5
1.155	51.6
1.112	51.2
1.121	50.5
1.223	50.1
1.257	49.8
1.157	49.6
0.913	49.4
0.62	49.3
0.255	49.2
-0.28	49.3
-1.08	49.7
-1.551	50.3
-1.799	51.3
-1.825	52.8
-1.456	54.4
-0.944	56
-0.57	56.9
-0.431	57.5
-0.577	57.3
-0.96	56.6
-1.616	56
-1.875	55.4
-1.891	55.4
-1.746	56.4
-1.474	57.2
-1.201	58
-0.927	58.4
-0.524	58.4
0.04	58.1
0.788	57.7
0.943	57
0.93	56
1.006	54.7
1.137	53.2
1.198	52.1
1.054	51.6
0.595	51
-0.06	50.5
-0.314	50.4
-0.288	51
-0.153	51.8
-0.109	52.4
-0.187	53
-0.255	53.4
-0.229	53.6
-0.007	53.7
0.254	53.8

Table 1.5: continued(i)

gas flow rate	CO2 conc.
0.33	53.8
0.102	53.8
-0.423	53.3
-1.139	53
-2.275	52.9
-2.594	53.4
-2.716	54.6
-2.51	56.4
-1.79	58
-1.346	59.4
-1.081	60.2
-0.91	60
-0.876	59.4
-0.885	58.4
-0.8	57.6
-0.544	56.9
-0.416	56.4
-0.271	56
0	55.7
0.403	55.3
0.841	55
1.285	54.4
1.607	53.7
1.746	52.8
1.683	51.6
1.485	50.6
0.993	49.4
0.648	48.8
0.577	48.5
0.577	48.7
0.632	49.2
0.747	49.8
0.9	50.4
0.993	50.7
0.968	50.9
0.79	50.7
0.399	50.5
-0.161	50.4
-0.553	50.2
-0.603	50.4
-0.424	51.2
-0.194	52.3
-0.049	53.2
0.06	53.9
0.161	54.1
0.301	54
0.517	53.6
0.566	53.2
0.56	53
0.573	52.8
0.592	52.3
0.671	51.9
0.933	51.6
1.337	51.6

Table 1.5:continued(ii)

Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.simplregr.v1.pol	6.03	0.57	2.1	4.58	19.52	1.98	1.02	4.1	0.21	3.25	2.08	6.18	2.02	0.96
ica.simplregr.v1.sin	5.74	0.57	2.09	4.86	18.87	1.44	1.02	2.82	0.1	2.22	1.37	4.2	1.45	0.97
ica.simplregr.v1.tnh	5.56	0.57	2.09	5.06	18.42	0.93	1.02	1.57	0.03	1.12	0.24	1.81	1.33	0.98
ica.simplregr.v1.exp	3.23	0.18	1.19	2.83	10.63	0.14	1.02	7.68	0.6	5.46	0.85	8.53	6.83	0.92
ica.simplregr.v2.pol	6.33	0.65	2.24	5.04	20.7	0.94	1.04	2.8	0.12	2.5	2.15	4.95	0.65	0.97
ica.simplregr.v2.sin	6.06	0.65	2.23	5.29	20.04	0.09	1.04	1.49	0.04	1.49	1.49	2.98	0	0.99
ica.simplregr.v2.tnh	5.97	0.65	2.23	5.4	19.58	0.61	1.04	0.36	0	0.3	0.23	0.59	0.14	1
ica.simplregr.v2.exp	3.86	0.26	1.42	3.36	12.32	0.74	1.03	6.23	0.4	4.46	1.02	7.25	5.21	0.94
ica.simplregr.v3.pol	2.73	0.09	0.81	1.06	4.56	0.98	0.98	7.14	0.87	6.59	5.99	13.13	1.15	0.94
ica.simplregr.v3.sin	3.4	0.13	1	1.23	5.67	1.58	0.98	4.71	0.23	3.37	0.71	5.42	4	0.95
ica.simplregr.v3.tnh	3.86	0.18	1.17	1.66	6.56	1.57	0.98	5.06	0.36	4.27	3.29	8.35	1.77	0.97
ica.simplregr.v3.exp	2.45	0.07	0.74	1.1	4.37	0.22	0.98	16.68	2.9	12.04	3.4	20.09	13.28	0.83
ica.simplregr.v4.pol	2.69	0.09	0.81	1.16	4.78	0.54	0.98	7.08	0.9	6.7	6.3	13.38	0.79	0.94
ica.simplregr.v4.sin	3.38	0.13	1	1.25	5.38	1.52	0.98	4.99	0.26	3.59	0.96	5.94	4.03	0.95
ica.simplregr.v4.tnh	3.85	0.18	1.16	1.65	6.29	1.35	0.98	5.41	0.42	4.57	3.54	8.94	1.87	0.96
ica.simplregr.v4.exp	2.47	0.07	0.76	1.17	4.58	0.39	0.98	17.25	3.11	12.48	3.71	20.96	13.54	0.83
ica.simplregr.v5.pol	1.43	0.04	0.54	1.33	4.75	0.05	1	7.31	0.67	5.8	3.71	11.02	3.61	0.96
ica.simplregr.v5.sin	2.02	0.09	0.82	2.17	6.56	0.04	1	2.4	0.06	1.77	0.73	3.13	1.67	0.98
ica.simplregr.v5.tnh	2.53	0.14	1.03	2.73	8.72	0.1	1	5.18	0.28	3.72	0.95	6.13	4.23	0.99
ica.simplregr.v5.exp	1.07	0.02	0.39	0.92	3.42	0.1	1	14.66	2.27	10.66	3.48	18.15	11.18	0.85
ica.cr.fc.v1.pol.nc2	2.37	0.08	0.78	1.53	5.43	0.29	1.02	12.19	1.88	9.68	6.25	18.43	5.94	1.06
ica.cr.fc.v1.pol.nc3	1.95	0.06	0.66	1.38	5.43	0.62	1.02	15.88	2.59	11.38	2.55	18.43	13.34	1.16
ica.cr.fc.v1.pol.nc4	1.85	0.05	0.63	1.32	5.11	0.48	1.02	11.04	1.27	7.97	2.3	13.34	8.74	1.11
ica.cr.fc.v1.pol.nc5	1.84	0.05	0.63	1.32	5.11	0.48	1.02	13.25	1.75	9.37	0.09	13.34	13.15	1.13
ica.cr.fc.v1.sin.nc2	2.39	0.08	0.78	1.5	5.31	0.09	1.02	10.72	1.39	8.33	4.88	15.6	5.83	1.11
ica.cr.fc.v1.sin.nc3	2	0.06	0.67	1.34	5.31	0.44	1.02	13.05	1.77	9.4	2.55	15.6	10.5	1.13
ica.cr.fc.v1.sin.nc4	1.89	0.05	0.63	1.28	5.04	0.67	1.02	9.37	0.89	6.67	1.13	10.5	8.24	1.09
ica.cr.fc.v1.sin.nc5	1.76	0.05	0.6	1.27	5.04	0.36	1.02	5.73	0.39	4.42	2.5	8.24	3.23	1.03
ica.cr.fc.v1.tnh.nc2	2.39	0.08	0.78	1.46	5.23	0.03	1.02	12.41	1.55	8.81	1.19	13.6	11.22	1.12
ica.cr.fc.v1.tnh.nc3	2.02	0.06	0.67	1.33	5.23	0.4	1.02	11.21	1.31	8.1	2.39	13.6	8.81	1.11
ica.cr.fc.v1.tnh.nc4	1.93	0.05	0.64	1.26	4.98	0.71	1.02	8.62	0.74	6.09	0.2	8.81	8.42	1.09
ica.cr.fc.v1.tnh.nc5	1.79	0.05	0.61	1.29	4.98	0.23	1.02	5.7	0.4	4.47	2.73	8.42	2.97	1.03
ica.cr.fc.v1.exp.nc2	1.58	0.03	0.45	0.37	2.22	0.96	1.02	23.79	6.24	17.66	7.62	31.4	16.17	0.92
ica.cr.fc.v1.exp.nc3	1.57	0.03	0.44	0.3	2.14	1.13	1.02	11.95	1.61	8.96	4.22	16.17	7.73	1.12

Table A : performance statistics of all models on problem of estimation of life of converter lining (ICA)

* simplregr = simple rigression, cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica= data prepared using mean with ICA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

as flow rate	CO2 conc.
1.46	51.4
1.353	51.2
0.772	50.7
0.218	50
-0.237	49.4
-0.714	49.3
-1.099	49.7
-1.269	50.6
-1.175	51.8
-0.676	53
0.033	54
0.556	55.3
0.643	55.9
0.484	55.9
0.109	54.6
-0.31	53.5
-0.697	52.4
-1.047	52.1
-1.218	52.3
-1.183	53
-0.873	53.8
-0.336	54.6
0.063	55.4
0.084	55.9
0	55.9
0.001	55.2
0.209	54.4
0.556	53.7
0.782	53.6
0.858	53.6
0.918	53.2
0.862	52.5
0.416	52
-0.336	51.4
-0.959	51
-1.813	50.9
-2.378	52.4
-2.499	53.5
-2.473	55.6
-2.33	58
-2.053	59.5
-1.739	60
-1.261	60.4
-0.569	60.5
-0.137	60.2
-0.024	59.7
-0.05	59
-0.135	57.6
-0.276	56.4
-0.534	55.2
-0.871	54.5
-1.243	54.1
-1.439	54.1
-1.422	54.4

able1.5:continued(iii)

gas flow rate	CO2 conc.
-1.175	55.2
-0.813	56.2
-0.634	57
-0.582	57.3
-0.625	57.4
-0.713	57
-0.848	56.4
-1.039	55.9
-1.346	55.5
-1.628	55.3
-1.619	55.2
-1.149	55.4
-0.488	56
-0.16	56.5
-0.007	57.1
-0.092	57.3
-0.62	56.8
-1.086	55.6
-1.525	55
-1.858	54.1
-2.029	54.3
-2.024	55.3
-1.961	56.4
-1.952	57.2
-1.794	57.8
-1.302	58.3
-1.03	58.6
-0.918	58.8
-0.798	58.8
-0.867	58.6
-1.047	58
-1.123	57.4
-0.876	57
-0.395	56.4
0.185	56.3
0.662	56.4
0.709	56.4
0.605	56
0.501	55.2
0.603	54
0.943	53
1.223	52
1.249	51.6
0.824	51.6
0.102	51.1
0.025	50.4
0.382	50
0.922	50
1.032	52
0.866	54
0.527	55.1
0.093	54.5
-0.458	52.8
-0.748	51.4

Table 1.5:continued(iv)

gas flow rate	CO2 conc.
-0.947	50.8
-1.029	51.2
-0.928	52
-0.645	52.8
-0.424	53.8
-0.276	54.5
-0.158	54.9
-0.033	54.9
0.102	54.8
0.251	54.4
0.28	53.7
0	53.3
-0.493	52.8
-0.579	52.6
-0.824	52.6
-0.74	53
-0.528	54.3
-0.204	56
0.034	57
0.204	58
0.253	58.6
0.195	58.5
0.131	58.3
0.017	57.8
-0.182	57.3
-0.262	57

Table 1.5:continued(v)

ica.cr.fc.v1.exp.nc5	1.56	0.02	0.44	0.27	2.03	1.14	1.02	8.47	0.72	6.02	0.75	9.22	7.73	1.08
ica.cr.fc.v2.pol.nc2	3.34	0.14	1.05	1.81	6.73	0.33	1.03	12.58	2.21	10.52	7.95	20.52	4.63	1.08
ica.cr.fc.v2.pol.nc3	3.05	0.12	0.96	1.66	6.73	0.33	1.03	17.5	3.15	12.56	3.03	20.52	14.47	1.17
ica.cr.fc.v2.pol.nc4	3.03	0.11	0.94	1.5	6.4	0.75	1.03	12.32	1.56	8.84	2.15	14.47	10.17	1.12
ica.cr.fc.v2.pol.nc5	3.03	0.11	0.94	1.5	6.4	0.75	1.03	14.62	2.14	10.34	0.15	14.78	14.47	1.15
ica.cr.fc.v2.sin.nc2	3.33	0.15	1.06	1.84	6.63	0.13	1.03	12.69	1.85	9.61	4.89	17.57	7.8	1.13
ica.cr.fc.v2.sin.nc3	3.06	0.12	0.97	1.68	6.63	0.13	1.03	14.56	2.21	10.51	3.02	17.57	11.54	1.15
ica.cr.fc.v2.sin.nc4	3.05	0.12	0.94	1.51	6.34	0.74	1.03	10.6	1.13	7.53	0.94	11.54	9.66	1.11
ica.cr.fc.v2.sin.nc5	3.02	0.11	0.92	1.38	6.34	0.74	1.03	5.82	0.49	4.93	3.84	9.66	1.97	1.04
ica.cr.fc.v2.tnh.nc2	3.33	0.14	1.05	1.83	6.56	0.09	1.03	14.51	2.11	10.28	0.97	15.48	13.54	1.15
ica.cr.fc.v2.tnh.nc3	3.07	0.12	0.97	1.68	6.56	0.09	1.03	12.63	1.68	9.16	2.85	15.48	9.79	1.13
ica.cr.fc.v2.tnh.nc4	3.06	0.12	0.95	1.53	6.29	0.62	1.03	9.83	0.97	6.95	0.04	9.87	9.79	1.1
ica.cr.fc.v2.tnh.nc5	3.03	0.11	0.93	1.41	6.29	0.62	1.03	5.78	0.5	5.01	4.08	9.87	1.7	1.04
ica.cr.fc.v2.exp.nc2	2.95	0.09	0.83	0.38	3.61	2.33	1.03	26.3	7.65	19.55	8.52	34.83	17.78	0.91
ica.cr.fc.v2.exp.nc3	2.93	0.09	0.82	0.31	3.52	2.47	1.03	13.88	2.08	10.2	3.9	17.78	9.98	1.14
ica.cr.fc.v2.exp.nc4	2.93	0.09	0.82	0.28	3.4	2.49	1.03	10.09	1.02	7.14	0.11	10.2	9.98	1.1
ica.cr.fc.v2.exp.nc5	2.92	0.09	0.81	0.27	3.4	2.49	1.03	10.09	1.02	7.14	0.11	10.2	9.98	1.1
ica.cr.fc.v3.pol.nc2	2.36	0.06	0.66	0.09	2.5	2.12	0.98	5.56	0.31	3.94	0.28	5.84	5.29	1
ica.cr.fc.v3.pol.nc3	2.36	0.06	0.66	0.1	2.5	2.12	0.98	4.11	0.2	3.15	1.72	5.84	2.39	1.04
ica.cr.fc.v3.pol.nc4	2.37	0.06	0.66	0.08	2.48	2.2	0.98	4.67	0.27	3.68	2.28	6.95	2.39	1.05
ica.cr.fc.v3.pol.nc5	2.37	0.06	0.66	0.08	2.48	2.2	0.98	4.85	0.3	3.85	2.46	7.31	2.39	1.05
ica.cr.fc.v3.sin.nc2	2.36	0.06	0.66	0.12	2.51	2.04	0.98	3.72	0.14	2.63	0.23	3.95	3.49	1
ica.cr.fc.v3.sin.nc3	2.36	0.06	0.66	0.13	2.52	2.04	0.98	3.37	0.11	2.39	0.11	3.49	3.26	1.03
ica.cr.fc.v3.sin.nc4	2.37	0.06	0.66	0.11	2.52	2.14	0.98	5.07	0.29	3.81	1.81	6.88	3.26	1.05
ica.cr.fc.v3.sin.nc5	2.37	0.06	0.66	0.11	2.5	2.14	0.98	6.81	0.46	4.81	0.08	6.88	6.73	1
ica.cr.fc.v3.tnh.nc2	2.36	0.06	0.66	0.15	2.51	1.99	0.98	2.78	0.08	1.97	0.1	2.88	2.67	1
ica.cr.fc.v3.tnh.nc3	2.36	0.06	0.66	0.16	2.55	1.99	0.98	3.39	0.12	2.45	0.71	4.1	2.67	1.03
ica.cr.fc.v3.tnh.nc4	2.36	0.06	0.66	0.13	2.55	2.1	0.98	5.43	0.31	3.95	1.33	6.76	4.1	1.05
ica.cr.fc.v3.tnh.nc5	2.37	0.06	0.66	0.12	2.53	2.1	0.98	6.67	0.44	4.71	0.09	6.76	6.57	1
ica.cr.fc.v3.exp.nc2	2.36	0.06	0.66	0.04	2.45	2.28	0.98	10.61	1.17	7.66	2.17	12.79	8.44	1.02
ica.cr.fc.v3.exp.nc3	2.36	0.06	0.66	0.04	2.45	2.28	0.98	7.64	0.85	6.51	5.15	12.79	2.48	1.05
ica.cr.fc.v3.exp.nc4	2.37	0.06	0.66	0.03	2.41	2.3	0.98	5.49	0.39	4.43	3.01	8.5	2.48	1.03
ica.cr.fc.v3.exp.nc5	2.37	0.06	0.66	0.03	2.41	2.3	0.98	5.49	0.39	4.43	3.01	8.5	2.48	1.03

Table A: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.cr.fc.v4.pol.nc2	2.43	0.06	0.68	0.33	2.97	1.63	0.98	5.82	0.34	4.12	0.12	5.94	5.7	1
ica.cr.fc.v4.pol.nc3	2.43	0.06	0.68	0.34	3.14	1.74	0.98	4.12	0.2	3.18	1.82	5.94	2.3	1.04
ica.cr.fc.v4.pol.nc4	2.43	0.06	0.68	0.33	3.14	1.74	0.98	4.63	0.27	3.67	2.33	6.97	2.3	1.05
ica.cr.fc.v4.pol.nc5	2.43	0.06	0.68	0.33	3.14	1.74	0.98	4.79	0.29	3.82	2.49	7.29	2.3	1.05
ica.cr.fc.v4.sin.nc2	2.43	0.06	0.68	0.32	2.97	1.64	0.98	3.93	0.16	2.79	0.4	4.33	3.53	1
ica.cr.fc.v4.sin.nc3	2.43	0.06	0.68	0.33	3.13	1.75	0.98	3.36	0.11	2.38	0.17	3.53	3.18	1.03
ica.cr.fc.v4.sin.nc4	2.43	0.06	0.68	0.32	3.13	1.75	0.98	5.04	0.29	3.8	1.86	6.9	3.18	1.05
ica.cr.fc.v4.sin.nc5	2.43	0.06	0.68	0.32	3.13	1.75	0.98	6.85	0.47	4.84	0.05	6.9	6.8	1
ica.cr.fc.v4.tnh.nc2	2.43	0.06	0.68	0.32	2.97	1.65	0.98	2.97	0.09	2.11	0.27	3.24	2.7	1
ica.cr.fc.v4.tnh.nc3	2.43	0.06	0.68	0.32	3.13	1.76	0.98	3.38	0.12	2.43	0.68	4.05	2.7	1.03
ica.cr.fc.v4.tnh.nc4	2.43	0.06	0.68	0.31	3.13	1.76	0.98	5.41	0.31	3.94	1.36	6.77	4.05	1.05
ica.cr.fc.v4.tnh.nc5	2.43	0.06	0.68	0.31	3.13	1.76	0.98	6.7	0.45	4.74	0.06	6.77	6.64	1
ica.cr.fc.v4.exp.nc2	2.43	0.06	0.68	0.36	2.97	1.6	0.98	10.99	1.25	7.91	2.06	13.06	8.93	1.02
ica.cr.fc.v4.exp.nc3	2.43	0.06	0.68	0.37	3.15	1.7	0.98	7.88	0.89	6.67	5.18	13.06	2.7	1.05
ica.cr.fc.v4.exp.nc4	2.43	0.06	0.68	0.36	3.15	1.7	0.98	5.62	0.4	4.48	2.93	8.55	2.7	1.03
ica.cr.fc.v4.exp.nc5	2.42	0.06	0.68	0.37	3.39	1.82	0.98	5.62	0.4	4.48	2.93	8.55	2.7	1.03
ica.cr.fc.v5.pol.nc2	0.07	0	0.03	0.07	0.25	0	1	5.7	0.4	4.46	2.71	8.4	2.99	1.03
ica.cr.fc.v5.pol.nc3	0.08	0	0.03	0.06	0.25	0.01	1	6.64	0.47	4.86	1.76	8.4	4.88	1.07
ica.cr.fc.v5.pol.nc4	0.07	0	0.02	0.05	0.17	0	1	7.21	0.57	5.36	2.34	9.55	4.88	1.07
ica.cr.fc.v5.pol.nc5	0.07	0	0.02	0.05	0.17	0.01	1	7.39	0.61	5.52	2.52	9.91	4.88	1.07
ica.cr.fc.v5.sin.nc2	0.09	0	0.04	0.09	0.33	0	1	3.81	0.19	3.11	2.19	6	1.62	1.02
ica.cr.fc.v5.sin.nc3	0.11	0	0.04	0.08	0.33	0.03	1	5.88	0.35	4.16	0.12	6	5.76	1.06
ica.cr.fc.v5.sin.nc4	0.09	0	0.03	0.07	0.23	0.01	1	7.62	0.61	5.55	1.86	9.48	5.76	1.08
ica.cr.fc.v5.sin.nc5	0.08	0	0.03	0.07	0.23	0.01	1	6.97	0.55	5.24	2.5	9.48	4.47	1.03
ica.cr.fc.v5.tnh.nc2	0.11	0	0.04	0.1	0.39	0	1	2.85	0.13	2.6	2.32	5.16	0.53	1.02
ica.cr.fc.v5.tnh.nc3	0.13	0	0.04	0.1	0.39	0.04	1	5.9	0.35	4.2	0.73	6.63	5.16	1.06
ica.cr.fc.v5.tnh.nc4	0.1	0	0.04	0.08	0.28	0.02	1	7.99	0.66	5.73	1.36	9.35	6.63	1.08
ica.cr.fc.v5.tnh.nc5	0.1	0	0.04	0.08	0.28	0.02	1	6.83	0.53	5.15	2.52	9.35	4.31	1.03
ica.cr.fc.v5.exp.nc2	0.03	0	0.01	0.03	0.09	0	1	10.87	1.4	8.36	4.65	15.52	6.22	1.05
ica.cr.fc.v5.exp.nc3	0.03	0	0.01	0.03	0.09	0	1	7.82	1.2	7.76	7.7	15.52	0.12	1.08
ica.cr.fc.v5.exp.nc4	0.02	0	0.01	0.02	0.07	0	1	5.63	0.62	5.57	5.51	11.13	0.12	1.06
ica.cr.fc.v5.exp.nc5	0.02	0	0.01	0.02	0.07	0	1	5.63	0.62	5.57	5.51	11.13	0.12	1.06
ica.cr.km.v1.pol.nc2	3.04	0.17	1.13	2.74	8.69	0.04	1.02	22.54	6.48	18	11.83	34.36	10.71	1.23
ica.cr.km.v1.pol.nc3	2.02	0.06	0.68	1.39	4.53	0.12	1.02	9.63	1.72	9.27	8.9	18.53	0.73	1.09

Table A : continued

cr = cluster wise regression, fc = fuzzy c-means clustering,km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.cr.km.v1.pol.nc4	1.8	0.05	0.6	1.22	5.11	0.43	1.02	8.4	0.71	5.95	0.34	8.74	8.06	1
ica.cr.km.v1.pol.nc5	1.8	0.05	0.6	1.22	5.11	0.43	1.02	11.52	1.45	8.51	3.46	14.98	8.06	1.03
ica.cr.km.v1.sin.nc2	2.39	0.08	0.78	1.5	5.31	0.09	1.02	10.72	1.39	8.33	4.88	15.6	5.83	1.11
ica.cr.km.v1.sin.nc3	2.09	0.07	0.71	1.48	4.91	0.12	1.02	9.77	1.28	8	5.71	15.48	4.06	1.1
ica.cr.km.v1.sin.nc4	1.87	0.05	0.61	1.18	5.04	0.55	1.02	7.9	0.63	5.59	0.33	8.24	7.57	1
ica.cr.km.v1.sin.nc5	1.86	0.05	0.61	1.18	5.04	0.55	1.02	11.66	1.53	8.74	4.1	15.76	7.57	1.04
ica.cr.km.v1.tnh.nc2	2.39	0.08	0.78	1.46	5.23	0.03	1.02	12.41	1.55	8.81	1.19	13.6	11.22	1.12
ica.cr.km.v1.tnh.nc3	2.11	0.07	0.72	1.53	5.11	0.09	1.02	9.98	1.12	7.48	3.52	13.49	6.46	1.1
ica.cr.km.v1.tnh.nc4	1.91	0.05	0.62	1.16	4.98	0.61	1.02	7.72	0.6	5.48	0.7	8.42	7.02	1.01
ica.cr.km.v1.tnh.nc5	1.91	0.05	0.62	1.16	4.98	0.61	1.02	10.11	1.12	7.48	3.09	13.2	7.02	1.03
ica.cr.km.v1.exp.nc2	1.67	0.04	0.53	0.94	3.9	0.23	1.02	18.12	5.86	17.11	16.04	34.17	2.08	1.16
ica.cr.km.v1.exp.nc3	1.57	0.03	0.44	0.34	2.15	1.04	1.02	12.54	1.7	9.22	3.55	16.09	8.99	1.04
ica.cr.km.v1.exp.nc4	1.56	0.03	0.44	0.28	2.03	1.14	1.02	8.47	0.72	6.02	0.75	9.22	7.73	1.08
ica.cr.km.v1.exp.nc5	1.56	0.03	0.44	0.28	2.03	1.14	1.02	10.47	1.17	7.65	2.74	13.21	7.73	1.1
ica.cr.km.v2.pol.nc2	3.78	0.24	1.35	3.04	10.02	0.03	1.03	24.34	7.48	19.34	12.47	36.81	11.87	1.24
ica.cr.km.v2.pol.nc3	3.06	0.12	0.98	1.73	5.84	0.18	1.03	10.64	2.12	10.3	9.94	20.58	0.7	1.1
ica.cr.km.v2.pol.nc4	3.03	0.11	0.92	1.37	6.4	0.92	1.03	9.08	0.84	6.47	1.09	10.17	7.99	1.01
ica.cr.km.v2.pol.nc5	3.02	0.11	0.92	1.37	6.4	0.92	1.03	12.41	1.73	9.31	4.42	16.82	7.99	1.04
ica.cr.km.v2.sin.nc2	3.33	0.15	1.06	1.84	6.63	0.13	1.03	12.69	1.85	9.61	4.89	17.57	7.8	1.13
ica.cr.km.v2.sin.nc3	3.08	0.13	1	1.86	6.21	0.12	1.03	10.92	1.61	8.98	6.49	17.41	4.43	1.11
ica.cr.km.v2.sin.nc4	3.04	0.11	0.93	1.41	6.34	0.74	1.03	8.52	0.74	6.08	1.14	9.66	7.39	1.01
ica.cr.km.v2.sin.nc5	3.04	0.11	0.93	1.4	6.34	0.74	1.03	12.53	1.83	9.57	5.14	17.67	7.39	1.05
ica.cr.km.v2.tnh.nc2	3.33	0.14	1.05	1.83	6.56	0.09	1.03	14.51	2.11	10.28	0.97	15.48	13.54	1.15
ica.cr.km.v2.tnh.nc3	3.09	0.13	1.01	1.92	6.41	0.05	1.03	11.18	1.42	8.43	4.17	15.34	7.01	1.11
ica.cr.km.v2.tnh.nc4	3.05	0.11	0.94	1.44	6.29	0.62	1.03	8.33	0.72	5.99	1.54	9.87	6.79	1.02
ica.cr.km.v2.tnh.nc5	3.05	0.11	0.93	1.44	6.29	0.62	1.03	10.8	1.33	8.15	4.01	14.81	6.79	1.04
ica.cr.km.v2.exp.nc2	3	0.1	0.88	1	5.27	1.17	1.03	18.59	6.78	18.41	18.23	36.82	0.37	1.18
ica.cr.km.v2.exp.nc3	2.94	0.09	0.82	0.34	3.54	2.4	1.03	13.27	1.95	9.88	4.36	17.63	8.91	1.04
ica.cr.km.v2.exp.nc4	2.93	0.09	0.82	0.28	3.4	2.49	1.03	10.09	1.02	7.14	0.11	10.2	9.98	1.1
ica.cr.km.v2.exp.nc5	2.93	0.09	0.82	0.28	3.4	2.49	1.03	12.4	1.6	8.93	2.42	14.82	9.98	1.12
ica.cr.km.v3.pol.nc2	2.31	0.06	0.69	0.93	3.44	0.17	0.98	12.27	2.17	10.42	8.17	20.43	4.1	1.12
ica.cr.km.v3.pol.nc3	2.36	0.06	0.66	0.13	2.54	2.09	0.98	4.51	0.21	3.24	0.81	5.32	3.7	1.01
ica.cr.km.v3.pol.nc4	2.37	0.06	0.66	0.07	2.46	2.2	0.98	5.21	0.3	3.88	1.74	6.95	3.46	1.02
ica.cr.km.v3.pol.nc5	2.37	0.06	0.66	0.07	2.46	2.2	0.98	5.31	0.32	3.98	1.85	7.17	3.46	1.02

Table A : continued

cr = cluster wise regression,km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.cr.km.v3.sin.nc2	2.36	0.06	0.66	0.12	2.51	2.04	0.98	3.72	0.14	2.63	0.23	3.95	3.49	1
ica.cr.km.v3.sin.nc3	2.36	0.06	0.66	0.17	2.6	1.98	0.98	2.06	0.05	1.58	0.87	2.92	1.19	1.01
ica.cr.km.v3.sin.nc4	2.37	0.06	0.66	0.09	2.49	2.14	0.98	4.75	0.27	3.68	2.14	6.88	2.61	1.02
ica.cr.km.v3.sin.nc5	2.37	0.06	0.66	0.09	2.49	2.14	0.98	5	0.31	3.92	2.39	7.4	2.61	1.02
ica.cr.km.v3.tnh.nc2	2.36	0.06	0.66	0.15	2.51	1.99	0.98	2.78	0.08	1.97	0.1	2.88	2.67	1
ica.cr.km.v3.tnh.nc3	2.36	0.06	0.66	0.19	2.65	1.89	0.98	1.48	0.03	1.14	0.62	2.1	0.87	1.01
ica.cr.km.v3.tnh.nc4	2.36	0.06	0.66	0.11	2.52	2.1	0.98	4.3	0.25	3.5	2.46	6.76	1.84	1.02
ica.cr.km.v3.tnh.nc5	2.37	0.06	0.66	0.11	2.52	2.1	0.98	4.88	0.33	4.06	3.04	7.91	1.84	1.03
ica.cr.km.v3.exp.nc2	2.34	0.06	0.66	0.3	2.88	1.75	0.98	17	3.66	13.54	8.79	25.79	8.21	1.09
ica.cr.km.v3.exp.nc3	2.36	0.06	0.66	0.05	2.44	2.27	0.98	11.15	1.28	7.99	1.79	12.94	9.37	1.02
ica.cr.km.v3.exp.nc4	2.37	0.06	0.66	0.03	2.41	2.3	0.98	5.49	0.39	4.43	3.01	8.5	2.48	1.03
ica.cr.km.v3.exp.nc5	2.37	0.06	0.66	0.03	2.41	2.3	0.98	5.52	0.4	4.46	3.04	8.56	2.48	1.03
ica.cr.km.v4.pol.nc2	2.38	0.06	0.7	0.86	3.54	0.49	0.98	12.4	2.2	10.49	8.14	20.53	4.26	1.12
ica.cr.km.v4.pol.nc3	2.42	0.06	0.68	0.32	3.14	1.74	0.98	4.66	0.22	3.33	0.71	5.36	3.95	1.01
ica.cr.km.v4.pol.nc4	2.43	0.06	0.68	0.33	3.06	1.7	0.98	5.33	0.31	3.94	1.63	6.97	3.7	1.02
ica.cr.km.v4.pol.nc5	2.43	0.06	0.68	0.32	3.06	1.7	0.98	5.47	0.33	4.07	1.78	7.25	3.7	1.02
ica.cr.km.v4.sin.nc2	2.43	0.06	0.68	0.32	2.97	1.64	0.98	3.93	0.16	2.79	0.4	4.33	3.53	1
ica.cr.km.v4.sin.nc3	2.42	0.06	0.68	0.31	3.13	1.75	0.98	2.14	0.05	1.61	0.76	2.9	1.38	1.01
ica.cr.km.v4.sin.nc4	2.43	0.06	0.68	0.31	3.05	1.72	0.98	4.86	0.28	3.73	2.04	6.9	2.82	1.02
ica.cr.km.v4.sin.nc5	2.43	0.06	0.68	0.31	3.05	1.72	0.98	5.16	0.32	4	2.33	7.49	2.82	1.02
ica.cr.km.v4.tnh.nc2	2.43	0.06	0.68	0.32	2.97	1.65	0.98	2.97	0.09	2.11	0.27	3.24	2.7	1
ica.cr.km.v4.tnh.nc3	2.42	0.06	0.68	0.31	3.13	1.76	0.98	1.39	0.02	1.09	0.67	2.06	0.73	1.01
ica.cr.km.v4.tnh.nc4	2.43	0.06	0.68	0.31	3.04	1.73	0.98	4.4	0.25	3.53	2.36	6.77	2.04	1.02
ica.cr.km.v4.tnh.nc5	2.43	0.06	0.68	0.31	3.04	1.73	0.98	4.97	0.33	4.08	2.93	7.91	2.04	1.03
ica.cr.km.v4.exp.nc2	2.42	0.06	0.68	0.38	3.07	1.66	0.98	17.19	3.74	13.67	8.84	26.03	8.35	1.09
ica.cr.km.v4.exp.nc3	2.43	0.06	0.68	0.36	3.15	1.7	0.98	11.46	1.34	8.19	1.7	13.16	9.76	1.02
ica.cr.km.v4.exp.nc4	2.43	0.06	0.68	0.36	3.15	1.7	0.98	5.62	0.4	4.48	2.93	8.55	2.7	1.03
ica.cr.km.v4.exp.nc5	2.43	0.06	0.68	0.36	3.15	1.7	0.98	5.69	0.41	4.55	2.99	8.68	2.7	1.03
ica.cr.km.v5.pol.nc2	0.64	0.01	0.27	0.72	2.26	0.01	1	14.99	2.95	12.14	8.37	23.35	6.62	1.15
ica.cr.km.v5.pol.nc3	0.11	0	0.04	0.08	0.29	0.02	1	4.62	0.32	4	3.26	7.88	1.36	1.03
ica.cr.km.v5.pol.nc4	0.06	0	0.02	0.04	0.17	0	1	5.33	0.46	4.81	4.21	9.55	1.12	1.04
ica.cr.km.v5.pol.nc5	0.06	0	0.02	0.04	0.17	0.01	1	5.44	0.48	4.91	4.32	9.76	1.12	1.04
ica.cr.km.v5.sin.nc2	0.09	0	0.04	0.09	0.33	0	1	3.81	0.19	3.11	2.19	6	1.62	1.02
ica.cr.km.v5.sin.nc3	0.13	0	0.05	0.1	0.4	0.03	1	3.31	0.15	2.77	2.11	5.42	1.21	1.03

Table A: continued

cr = cluster wise regression,km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.cr.km.v5.sin.nc4	0.07	0	0.03	0.06	0.23	0.01	1	4.86	0.45	4.74	4.61	9.48	0.25	1.05
ica.cr.km.v5.sin.nc5	0.07	0	0.03	0.06	0.23	0.02	1	5.12	0.5	5	4.88	10	0.25	1.05
ica.cr.km.v5.tnh.nc2	0.11	0	0.04	0.1	0.39	0	1	2.85	0.13	2.6	2.32	5.16	0.53	1.02
ica.cr.km.v5.tnh.nc3	0.15	0	0.06	0.13	0.49	0.02	1	3.95	0.16	2.83	0.63	4.58	3.32	1.04
ica.cr.km.v5.tnh.nc4	0.09	0	0.03	0.07	0.28	0.02	1	4.94	0.44	4.68	4.41	9.35	0.54	1.05
ica.cr.km.v5.tnh.nc5	0.09	0	0.03	0.07	0.28	0	1	5.53	0.56	5.27	5	10.53	0.54	1.06
ica.cr.km.v5.exp.nc2	0.22	0	0.08	0.21	0.63	0	1	17.42	4.34	14.73	11.43	28.85	5.99	1.11
ica.cr.km.v5.exp.nc3	0.04	0	0.01	0.03	0.1	0.01	1	11.42	1.49	8.62	4.26	15.68	7.17	1.04
ica.cr.km.v5.exp.nc4	0.02	0	0.01	0.02	0.07	0	1	5.63	0.62	5.57	5.51	11.13	0.12	1.06
ica.cr.km.v5.exp.nc5	0.02	0	0.01	0.02	0.07	0	1	5.66	0.63	5.6	5.54	11.2	0.12	1.06
ica.cr.kh.v1.pol.nc2	2.98	0.14	1.02	2.16	8.35	0.15	1.02	17.79	5.96	17.27	16.73	34.52	1.06	1.17
ica.cr.kh.v1.pol.nc3	2.66	0.11	0.94	2.09	7.72	0.33	1.02	9.16	0.84	6.48	0.51	9.66	8.65	0.91
ica.cr.kh.v1.pol.nc4	2.11	0.06	0.68	1.27	6.01	0.8	1.02	35.59	13.55	26.03	9.44	45.02	26.15	1.36
ica.cr.kh.v1.pol.nc5	2.58	0.1	0.86	1.7	6.89	0.38	1.02	20.66	4.96	15.74	8.28	28.95	12.38	1.08
ica.cr.kh.v1.sin.nc2	3.11	0.12	0.96	1.55	5.85	0.38	1.02	8.54	1.38	8.3	8.05	16.58	0.49	1.09
ica.cr.kh.v1.sin.nc3	2.35	0.1	0.86	2.03	7.57	0.02	1.02	7.08	0.53	5.16	1.74	8.82	5.34	0.93
ica.cr.kh.v1.sin.nc4	2.14	0.06	0.69	1.24	5.83	0.82	1.02	35.9	13.37	25.85	6.92	42.82	28.98	1.36
ica.cr.kh.v1.sin.nc5	2.73	0.11	0.91	1.81	6.96	0.45	1.02	19.33	4.57	15.12	9.15	28.48	10.18	1.09
ica.cr.kh.v1.tnh.nc2	3.04	0.12	0.95	1.55	5.74	0.38	1.02	9.89	1.15	7.59	4.18	14.07	5.71	1.1
ica.cr.kh.v1.tnh.nc3	2.42	0.09	0.85	1.85	6.99	0.03	1.02	14.62	3.7	13.61	12.51	27.13	2.11	0.85
ica.cr.kh.v1.tnh.nc4	2.69	0.1	0.89	1.77	7	0.83	1.02	28.85	8.35	20.43	1.61	30.46	27.23	1.29
ica.cr.kh.v1.tnh.nc5	2.8	0.11	0.93	1.87	7	0.5	1.02	18.16	4.12	14.35	9.08	27.23	9.08	1.09
ica.cr.kh.v1.exp.nc2	1.74	0.04	0.58	1.16	4.32	0.26	1.02	11.79	2.54	11.28	10.74	22.53	1.05	1.12
ica.cr.kh.v1.exp.nc3	1.63	0.03	0.5	0.81	3.58	0.49	1.02	4.33	0.19	3.06	0.12	4.44	4.21	1.04
ica.cr.kh.v1.exp.nc4	1.91	0.08	0.77	2.03	7.73	0.01	1.02	16.04	3.11	12.46	7.31	23.35	8.72	1.16
ica.cr.kh.v1.exp.nc5	1.62	0.03	0.5	0.81	3.78	0.47	1.02	20.41	5.93	17.22	13.28	33.69	7.13	1.2
ica.cr.kh.v2.pol.nc2	3.77	0.2	1.25	2.49	9.59	0.85	1.03	18.66	6.89	18.56	18.46	37.12	0.2	1.19
ica.cr.kh.v2.pol.nc3	3.47	0.18	1.18	2.48	8.96	0.41	1.03	8.39	0.71	5.96	0.81	9.2	7.57	0.92
ica.cr.kh.v2.pol.nc4	3.25	0.12	0.98	1.36	7.35	1.37	1.03	38.59	15.92	28.22	10.15	48.74	28.45	1.39
ica.cr.kh.v2.pol.nc5	3.46	0.16	1.11	2	8.24	0.18	1.03	20.89	5.39	16.41	10.11	31	10.78	1.1
ica.cr.kh.v2.sin.nc2	3.81	0.19	1.21	2.1	7.19	0.31	1.03	10.27	1.72	9.28	8.17	18.44	2.1	1.1
ica.cr.kh.v2.sin.nc3	3.32	0.16	1.12	2.3	8.83	0.63	1.03	6.17	0.4	4.48	1.45	7.62	4.71	0.94
ica.cr.kh.v2.sin.nc4	3.28	0.12	0.98	1.31	7.18	1.55	1.03	38.85	15.65	27.97	7.44	46.29	31.41	1.39
ica.cr.kh.v2.sin.nc5	3.63	0.17	1.15	2.03	8.35	0.38	1.03	19.5	5.03	15.86	11.08	30.58	8.42	1.11

Table A: continued

cr = cluster wise regression, km=k-means clustering,kh=som clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.cr.kh.v2.tnh.nc2	3.74	0.18	1.19	2.12	7.06	0.24	1.03	11.75	1.55	8.79	4.07	15.82	7.68	1.12
ica.cr.kh.v2.tnh.nc3	3.26	0.16	1.11	2.31	8.23	0.06	1.03	13.7	3.4	13.05	12.36	26.06	1.34	0.86
ica.cr.kh.v2.tnh.nc4	3.67	0.17	1.14	1.86	8.4	0.38	1.03	31.14	9.73	22.06	1.81	32.96	29.33	1.31
ica.cr.kh.v2.tnh.nc5	3.7	0.18	1.18	2.07	8.4	0.38	1.03	18.28	4.56	15.1	11.04	29.33	7.24	1.11
ica.cr.kh.v2.exp.nc2	3.07	0.11	0.92	1.24	5.73	1.05	1.03	13.45	2.94	12.12	10.64	24.08	2.81	1.13
ica.cr.kh.v2.exp.nc3	3	0.1	0.86	0.82	4.96	1.83	1.03	5.81	0.34	4.11	0.14	5.95	5.68	1.06
ica.cr.kh.v2.exp.nc4	3.06	0.14	1.05	2.24	9.14	0.03	1.03	17.59	3.69	13.57	7.69	25.28	9.9	1.18
ica.cr.kh.v2.exp.nc5	2.98	0.1	0.86	0.82	5.17	1.82	1.03	22.36	6.83	18.48	13.55	35.91	8.8	1.22
ica.cr.kh.v3.pol.nc2	2.34	0.06	0.66	0.37	3.02	1.48	0.98	16.91	3.46	13.16	7.76	24.67	9.15	1.08
ica.cr.kh.v3.pol.nc3	2.36	0.06	0.66	0.21	2.63	1.83	0.98	6.93	0.82	6.41	5.84	12.77	1.09	0.94
ica.cr.kh.v3.pol.nc4	2.36	0.06	0.67	0.55	3.25	0.75	0.98	12.24	1.89	9.72	6.26	18.51	5.98	1.12
ica.cr.kh.v3.pol.nc5	2.34	0.06	0.67	0.65	3.68	0.59	0.98	21.08	4.51	15.02	2.63	23.71	18.45	0.97
ica.cr.kh.v3.sin.nc2	2.34	0.06	0.66	0.44	3.23	1.21	0.98	8.04	0.65	5.7	0.58	8.62	7.46	1.01
ica.cr.kh.v3.sin.nc3	2.35	0.06	0.66	0.26	2.68	1.65	0.98	9.18	1.27	7.98	6.55	15.73	2.63	0.93
ica.cr.kh.v3.sin.nc4	2.36	0.06	0.67	0.53	3.26	0.82	0.98	15.27	2.5	11.19	4.12	19.4	11.15	1.15
ica.cr.kh.v3.sin.nc5	2.34	0.06	0.67	0.64	3.75	0.69	0.98	19.97	4.03	14.2	2.04	22.01	17.93	0.98
ica.cr.kh.v3.tnh.nc2	2.34	0.06	0.66	0.44	3.18	1.2	0.98	6.56	0.43	4.66	0.66	7.22	5.9	1.01
ica.cr.kh.v3.tnh.nc3	2.36	0.06	0.66	0.21	2.67	1.83	0.98	19.92	6.65	18.24	16.38	36.3	3.54	0.84
ica.cr.kh.v3.tnh.nc4	2.35	0.06	0.67	0.6	3.72	0.78	0.98	18.68	3.51	13.25	1.36	20.04	17.32	1.19
ica.cr.kh.v3.tnh.nc5	2.34	0.06	0.67	0.62	3.72	0.78	0.98	19.12	3.69	13.58	1.8	20.93	17.32	0.98
ica.cr.kh.v3.exp.nc2	2.28	0.06	0.68	0.93	3.86	0.35	0.98	11.14	1.72	9.29	6.96	18.1	4.18	1.07
ica.cr.kh.v3.exp.nc3	2.34	0.06	0.67	0.53	3.32	0.84	0.98	0.48	0	0.35	0.1	0.59	0.38	1
ica.cr.kh.v3.exp.nc4	2.89	0.1	0.86	1.09	5.04	0.81	0.98	12.52	2.02	10.04	6.72	19.23	5.8	1.13
ica.cr.kh.v3.exp.nc5	2.34	0.06	0.67	0.59	3.39	0.65	0.98	15.79	3.69	13.58	10.94	26.73	4.85	1.16
ica.cr.kh.v4.pol.nc2	2.41	0.06	0.68	0.38	3.21	1.75	0.98	17.16	3.56	13.33	7.81	24.97	9.36	1.08
ica.cr.kh.v4.pol.nc3	2.43	0.06	0.68	0.31	3.13	1.93	0.98	6.93	0.86	6.56	6.16	13.1	0.77	0.94
ica.cr.kh.v4.pol.nc4	2.39	0.06	0.68	0.53	3.06	0.95	0.98	12.57	1.97	9.92	6.25	18.82	6.32	1.13
ica.cr.kh.v4.pol.nc5	2.37	0.06	0.68	0.58	3.34	0.92	0.98	21.56	4.72	15.36	2.6	24.16	18.96	0.97
ica.cr.kh.v4.sin.nc2	2.4	0.06	0.68	0.4	2.97	1.69	0.98	8.36	0.7	5.92	0.43	8.79	7.93	1
ica.cr.kh.v4.sin.nc3	2.42	0.06	0.68	0.31	3.15	1.94	0.98	9.24	1.33	8.15	6.89	16.13	2.35	0.93
ica.cr.kh.v4.sin.nc4	2.39	0.06	0.68	0.5	3.03	1.01	0.98	15.67	2.62	11.45	4.06	19.73	11.61	1.16
ica.cr.kh.v4.sin.nc5	2.37	0.06	0.68	0.57	3.41	1.03	0.98	20.43	4.21	14.51	1.99	22.42	18.44	0.98
ica.cr.kh.v4.tnh.nc2	2.4	0.06	0.68	0.39	2.92	1.67	0.98	6.84	0.47	4.85	0.51	7.35	6.33	1.01
ica.cr.kh.v4.tnh.nc3	2.43	0.06	0.68	0.31	3.05	1.87	0.98	20.22	6.96	18.66	16.95	37.17	3.28	0.83

Table A : continued

cr = cluster wise regression, kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.cr.kh.v4.tnh.nc4	2.39	0.06	0.68	0.56	3.37	1.12	0.98	19.1	3.66	13.54	1.29	20.39	17.81	1.19
ica.cr.kh.v4.tnh.nc5	2.37	0.06	0.68	0.54	3.37	1.12	0.98	19.56	3.86	13.89	1.75	21.31	17.81	0.98
ica.cr.kh.v4.exp.nc2	2.35	0.06	0.69	0.78	3.45	0.59	0.98	11.25	1.75	9.37	6.98	18.24	4.27	1.07
ica.cr.kh.v4.exp.nc3	2.4	0.06	0.68	0.51	3.09	1.25	0.98	0.29	0	0.24	0.19	0.48	0.09	1
ica.cr.kh.v4.exp.nc4	2.87	0.1	0.86	1.19	4.93	0.59	0.98	12.75	2.09	10.22	6.81	19.56	5.94	1.13
ica.cr.kh.v4.exp.nc5	2.4	0.06	0.68	0.52	3.25	1.28	0.98	15.75	3.68	13.56	10.94	26.69	4.81	1.16
ica.cr.kh.v5.pol.nc2	0.26	0	0.1	0.27	0.91	0	1	17.32	4.08	14.28	10.37	27.69	6.95	1.1
ica.cr.kh.v5.pol.nc3	0.16	0	0.06	0.14	0.55	0.01	1	7.1	0.63	5.61	3.56	10.66	3.54	0.96
ica.cr.kh.v5.pol.nc4	0.31	0	0.16	0.46	1.65	0.01	1	14.96	2.65	11.51	6.42	21.38	8.55	1.15
ica.cr.kh.v5.pol.nc5	0.41	0	0.18	0.53	1.82	0	1	21.59	4.66	15.27	0.27	21.86	21.32	1
ica.cr.kh.v5.sin.nc2	0.3	0	0.13	0.34	1.18	0.03	1	8.24	0.77	6.2	3.02	11.26	5.22	1.03
ica.cr.kh.v5.sin.nc3	0.19	0	0.07	0.19	0.73	0.02	1	9.41	1.07	7.31	4.29	13.69	5.12	0.96
ica.cr.kh.v5.sin.nc4	0.3	0	0.15	0.45	1.59	0.01	1	18.07	3.44	13.12	4.22	22.29	13.85	1.18
ica.cr.kh.v5.sin.nc5	0.4	0	0.18	0.52	1.72	0	1	20.46	4.19	14.47	0.34	20.79	20.12	1
ica.cr.kh.v5.tnh.nc2	0.3	0	0.13	0.34	1.2	0.01	1	6.72	0.55	5.23	3.1	9.82	3.62	1.03
ica.cr.kh.v5.tnh.nc3	0.17	0	0.06	0.14	0.55	0	1	20.4	6.22	17.64	14.35	34.76	6.05	0.86
ica.cr.kh.v5.tnh.nc4	0.34	0	0.17	0.51	1.62	0	1	21.56	4.67	15.28	1.39	22.95	20.17	1.22
ica.cr.kh.v5.tnh.nc5	0.39	0	0.18	0.5	1.62	0.01	1	19.59	3.84	13.86	0.58	20.17	19.01	1.01
ica.cr.kh.v5.exp.nc2	0.68	0.01	0.27	0.67	2.06	0.03	1	11.41	2.21	10.52	9.55	20.96	1.86	1.1
ica.cr.kh.v5.exp.nc3	0.35	0	0.15	0.42	1.57	0.06	1	2.32	0.06	1.68	0.5	2.82	1.82	1.02
ica.cr.kh.v5.exp.nc4	1.33	0.05	0.6	1.69	5.74	0.01	1	15.25	2.8	11.83	6.88	22.13	8.37	1.15
ica.cr.kh.v5.exp.nc5	0.36	0	0.17	0.49	1.76	0.01	1	18.6	4.71	15.35	11.21	29.8	7.39	1.19
ica.cr.at.v1.pol.nc5	1.67	0.04	0.58	1.23	5.11	0.12	1.02	5.82	0.42	4.61	2.92	8.74	2.9	1.03
ica.cr.at.v1.sin.nc5	1.98	0.06	0.66	1.34	5.31	0.44	1.02	13.05	1.77	9.4	2.55	15.6	10.5	1.13
ica.cr.at.v1.tnh.nc5	1.88	0.05	0.64	1.32	5.23	0.05	1.02	7.07	0.93	6.8	6.52	13.6	0.55	1.07
ica.cr.at.v1.exp.nc5	1.53	0.02	0.43	0.2	2	1.18	1.02	8.25	0.93	6.82	4.98	13.23	3.28	1.05
ica.cr.at.v2.pol.nc5	2.96	0.1	0.9	1.3	6.4	0.92	1.03	6.41	0.55	5.26	3.76	10.17	2.65	1.04
ica.cr.at.v2.sin.nc5	3.04	0.12	0.96	1.67	6.63	0.13	1.03	14.56	2.21	10.51	3.02	17.57	11.54	1.15
ica.cr.at.v2.tnh.nc5	3.04	0.12	0.95	1.55	6.56	0.09	1.03	7.82	1.2	7.74	7.66	15.48	0.16	1.08
ica.cr.at.v2.exp.nc5	2.9	0.08	0.81	0.21	3.37	2.54	1.03	8.7	1.14	7.55	6.19	14.89	2.51	1.06
ica.cr.at.v3.pol.nc5	2.38	0.06	0.66	0.06	2.46	2.2	0.98	4.87	0.28	3.75	2.08	6.95	2.79	1.05
ica.cr.at.v3.sin.nc5	2.36	0.06	0.66	0.13	2.52	2.04	0.98	3.37	0.11	2.39	0.11	3.49	3.26	1.03
ica.cr.at.v3.tnh.nc5	2.37	0.06	0.66	0.14	2.51	1.99	0.98	3.53	0.13	2.57	0.85	4.38	2.67	1.04
ica.cr.at.v3.exp.nc5	2.37	0.06	0.66	0.02	2.39	2.34	0.98	6.47	0.45	4.76	1.83	8.3	4.64	1.02

Table A : continued

cr = cluster wise regression,kh=SOM clustering, at=A.R.T.2 clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.cr.at.v4.pol.nc5	2.39	0.06	0.67	0.17	2.71	2.08	0.98	4.77	0.28	3.71	2.19	6.97	2.58	1.05
ica.cr.at.v4.sin.nc5	2.41	0.06	0.67	0.28	3.1	1.96	0.98	3.36	0.11	2.38	0.17	3.53	3.18	1.03
ica.cr.at.v4.tnh.nc5	2.42	0.06	0.68	0.31	2.95	1.75	0.98	3.45	0.12	2.5	0.75	4.2	2.7	1.03
ica.cr.at.v4.exp.nc5	2.38	0.06	0.66	0.19	2.78	2.07	0.98	6.48	0.45	4.76	1.82	8.3	4.67	1.02
ica.cr.at.v5.pol.nc5	0.04	0	0.02	0.04	0.17	0	1	7.42	0.6	5.46	2.13	9.55	5.29	1.07
ica.cr.at.v5.sin.nc5	0.11	0	0.04	0.08	0.33	0.02	1	5.88	0.35	4.16	0.12	6	5.76	1.06
ica.cr.at.v5.tnh.nc5	0.11	0	0.04	0.09	0.39	0.03	1	6.04	0.37	4.31	0.87	6.91	5.16	1.06
ica.cr.at.v5.exp.nc5	0.01	0	0	0.01	0.03	0	1	6.63	0.62	5.59	4.3	10.93	2.33	1.04
ica.cr.fa.v1.pol.nc5	3.04	0.14	1.05	2.29	8.56	0.93	1.02	63.76	53.79	51.86	36.24	100	27.53	0.64
ica.cr.fa.v1.sin.nc5	2.95	0.12	0.97	1.91	6.98	0.79	1.02	50.56	50.01	50	49.44	100	1.12	0.51
ica.cr.fa.v1.tnh.nc5	2.87	0.12	0.96	1.95	6.92	0.67	1.02	51.12	50.03	50.01	48.88	100	2.24	0.51
ica.cr.fa.v1.exp.nc5	4.91	0.47	1.9	4.77	18.39	0.06	1.02	51.99	50.08	50.04	48.01	100	3.99	0.48
ica.cr.fa.v2.pol.nc5	3.8	0.21	1.28	2.61	9.88	0.4	1.03	64.73	54.34	52.13	35.27	100	29.46	0.65
ica.cr.fa.v2.sin.nc5	3.64	0.19	1.21	2.43	8.18	0.15	1.03	50.9	50.02	50.01	49.1	100	1.8	0.51
ica.cr.fa.v2.tnh.nc5	3.61	0.19	1.2	2.41	8.13	0.29	1.03	51.48	50.04	50.02	48.52	100	2.97	0.51
ica.cr.fa.v2.exp.nc5	5.58	0.56	2.07	4.96	19.98	0.49	1.03	51.31	50.03	50.02	48.69	100	2.62	0.49
ica.cr.fa.v3.pol.nc5	2.68	0.08	0.8	1.02	4.27	0.25	0.98	60.67	52.28	51.13	39.33	100	21.34	0.61
ica.cr.fa.v3.sin.nc5	2.32	0.06	0.68	0.73	3.38	0.29	0.98	51.47	50.04	50.02	48.53	100	2.95	0.51
ica.cr.fa.v3.tnh.nc5	2.32	0.06	0.68	0.78	3.53	0.15	0.98	51.89	50.07	50.04	48.11	100	3.79	0.52
ica.cr.fa.v3.exp.nc5	5.22	0.42	1.8	3.88	13.58	0.27	0.98	53.98	50.32	50.16	46.02	100	7.96	0.46
ica.cr.fa.v4.pol.nc5	2.68	0.08	0.8	1.09	4.46	0.18	0.98	60.6	52.25	51.11	39.4	100	21.2	0.61
ica.cr.fa.v4.sin.nc5	2.39	0.06	0.69	0.67	3.6	0.66	0.98	51.37	50.04	50.02	48.63	100	2.73	0.51
ica.cr.fa.v4.tnh.nc5	2.39	0.06	0.69	0.72	3.75	0.51	0.98	51.8	50.06	50.03	48.2	100	3.59	0.52
ica.cr.fa.v4.exp.nc5	5.23	0.42	1.81	3.88	13.58	0.94	0.98	54.27	50.37	50.18	45.73	100	8.55	0.46
ica.cr.fa.v5.pol.nc5	1.12	0.03	0.5	1.4	4.84	0	1	62.14	52.95	51.45	37.86	100	24.28	0.62
ica.cr.fa.v5.sin.nc5	0.5	0.01	0.21	0.56	2.12	0.09	1	52.72	50.15	50.07	47.28	100	5.45	0.53
ica.cr.fa.v5.tnh.nc5	0.54	0.01	0.22	0.6	2.27	0.09	1	53.15	50.2	50.1	46.85	100	6.3	0.53
ica.cr.fa.v5.exp.nc5	4.83	0.41	1.77	4.17	16.33	0.61	1	52.87	50.16	50.08	47.13	100	5.73	0.47

Table A : continued

cr = cluster wise regression, at=A.R.T.2 fa = fuzzy A.R.T clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics.						
ethod of modeling	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.oclstr.fc.nc1.e1	2.18	0.08	0.78	1.8	5.61	0.39	1	10.24	1.3	8.06	5.01	15.25	5.24	0.95
ica.oclstr.fc.nc1.e2	5.75	0.6	2.14	5.15	17.72	0.86	1	6.45	0.64	5.65	4.71	11.16	1.74	0.95
ica.oclstr.fc.nc1.e3	7.7	0.87	2.59	5.28	17.18	0.18	1.01	6.65	0.6	5.5	4.02	10.67	2.64	0.96
ica.oclstr.fc.nc1.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.fc.nc1.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.fc.nc2.e1	1	0.02	0.35	0.76	2.58	0.15	1	8.21	1	7.08	5.73	13.95	2.48	0.92
ica.oclstr.fc.nc2.e2	4.59	0.37	1.69	3.99	14.83	0.13	1	1.45	0.02	1.04	0.28	1.73	1.17	1.01
ica.oclstr.fc.nc2.e3	7.09	0.77	2.44	5.18	17.06	0.05	1.01	5.45	0.33	4.06	1.82	7.27	3.62	0.98
ica.oclstr.fc.nc2.e4	8.01	1.03	2.81	6.21	18.71	0.45	1.01	8.8	0.78	6.23	0.31	9.11	8.49	1
ica.oclstr.fc.nc2.e5	8.01	1.03	2.81	6.21	18.71	0.45	1.01	8.8	0.78	6.23	0.31	9.11	8.49	1
ica.oclstr.fc.nc3.e1	0.46	0.01	0.2	0.56	1.99	0.06	1	11.51	1.47	8.56	3.75	15.27	7.76	1.04
ica.oclstr.fc.nc3.e2	3.02	0.22	1.3	3.6	12.84	0.03	1	11.32	1.33	8.17	2.3	13.62	9.02	1.02
ica.oclstr.fc.nc3.e3	5.48	0.74	2.38	6.61	23.26	0.06	1.01	5.62	0.33	4.04	1	6.63	4.62	1.01
ica.oclstr.fc.nc3.e4	9.97	2.06	3.99	10.35	37.14	0.42	0.99	6.37	0.46	4.79	2.31	8.68	4.06	1.06
ica.oclstr.fc.nc3.e5	9.97	2.06	3.99	10.35	37.14	0.42	0.99	6.37	0.46	4.79	2.31	8.68	4.06	1.06
ica.oclstr.fc.nc4.e2	3.64	0.25	1.38	3.41	10.06	0.14	1.01	12.27	2.04	10.11	7.32	19.59	4.95	0.93
ica.oclstr.fc.nc4.e3	5.37	0.39	1.74	3.2	11.66	1.1	1.01	12.55	2.16	10.38	7.63	20.18	4.92	0.92
ica.oclstr.fc.nc4.e4	6.92	0.71	2.34	4.81	18.88	1.1	1.01	12.81	2.27	10.65	7.91	20.72	4.9	0.92
ica.oclstr.fc.nc4.e5	6.92	0.71	2.34	4.81	18.88	1.1	1.01	12.81	2.27	10.65	7.91	20.72	4.9	0.92
ica.oclstr.fc.nc5.e1	0.67	0.01	0.27	0.7	2.21	0	1	52.9	50.17	50.08	47.1	100	5.81	0.53
ica.oclstr.fc.nc5.e2	3.76	0.28	1.45	3.66	11.85	0.01	1.01	50.06	50	50	49.94	100	0.11	0.5
ica.oclstr.fc.nc5.e3	5.74	0.47	1.91	3.8	12.14	0.01	1.01	50.03	50	50	49.97	100	0.07	0.5
ica.oclstr.fc.nc5.e4	6.23	0.63	2.21	4.95	15.86	0.01	1.01	50.04	50	50	49.96	100	0.08	0.5
ica.oclstr.fc.nc5.e5	9.22	1.29	3.16	6.67	25.15	0.02	1.02	61.77	52.77	51.37	38.23	100	23.54	0.62
ica.oclstr.km.nc1.e1	2.18	0.08	0.78	1.8	5.61	0.39	1	10.24	1.3	8.06	5.01	15.25	5.24	0.95
ica.oclstr.km.nc1.e2	5.75	0.6	2.14	5.15	17.72	0.86	1	6.45	0.64	5.65	4.71	11.16	1.74	0.95
ica.oclstr.km.nc1.e3	7.7	0.87	2.59	5.28	17.18	0.18	1.01	6.65	0.6	5.5	4.02	10.67	2.64	0.96
ica.oclstr.km.nc1.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.km.nc1.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.km.nc2.e1	0.64	0.01	0.27	0.74	2.47	0	1	4.04	0.28	3.77	3.48	7.53	0.56	0.97
ica.oclstr.km.nc2.e2	1.28	0.03	0.45	1.03	3.64	0.13	1	3.95	0.28	3.77	3.57	7.52	0.38	0.96
ica.oclstr.km.nc2.e3	6.09	0.79	2.47	6.51	21.09	0.12	1.01	3.27	0.19	3.09	2.9	6.17	0.36	1.03
ica.oclstr.km.nc2.e4	12.23	1.93	3.86	6.63	24.88	0.36	1.02	1.8	0.03	1.27	0.1	1.9	1.69	1
ica.oclstr.km.nc2.e5	12.23	1.93	3.86	6.63	24.88	0.36	1.02	1.8	0.03	1.27	0.1	1.9	1.69	1

Table A: continued

oclstr=ortho-clustering, fc = fuzzy c-means clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)

nc = no. clusters, ica = data prepared using ICA,   mn error = mean error, ms error = mean squared error

rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modeling	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.oclstr.km.nc3.e1	0.82	0.02	0.43	1.32	4.97	0.01	1	21.68	8.18	20.22	18.66	40.33	3.02	1.22
ica.oclstr.km.nc3.e3	6.72	0.77	2.44	5.68	19.46	0.52	1.01	8.11	0.71	5.94	2.2	10.3	5.91	1.08
ica.oclstr.km.nc3.e4	7.7	0.97	2.73	6.11	20.08	0.52	1.01	11.62	1.37	8.27	1.31	12.93	10.31	1.12
ica.oclstr.km.nc3.e5	7.7	0.97	2.73	6.11	20.08	0.52	1.01	11.62	1.37	8.27	1.31	12.93	10.31	1.12
ica.oclstr.km.nc4.e1	0.4	0	0.15	0.35	1.23	0.01	1	15.12	2.33	10.8	2.17	17.29	12.95	0.98
ica.oclstr.km.nc4.e2	2.87	0.22	1.3	3.71	11.93	0.14	1	17.8	3.4	13.04	4.83	22.63	12.97	0.95
ica.oclstr.km.nc4.e3	4.68	0.53	2.02	5.59	14.95	0.14	1.01	13.78	1.91	9.76	0.82	14.6	12.96	0.99
ica.oclstr.km.nc4.e4	10.83	2.34	4.24	10.8	39.76	0.11	1.02	12.3	1.52	8.71	0.68	12.98	11.62	1.01
ica.oclstr.km.nc4.e5	10.83	2.34	4.24	10.8	39.76	0.11	1.02	12.3	1.52	8.71	0.68	12.98	11.62	1.01
ica.oclstr.km.nc5.e1	0.88	0.03	0.46	1.39	4.59	0	1	41.95	25.78	35.9	28.6	70.55	13.35	0.58
ica.oclstr.km.nc5.e2	3.12	0.22	1.31	3.52	12.9	0.05	1	39.6	22.19	33.31	25.51	65.11	14.1	0.6
ica.oclstr.km.nc5.e3	5.6	0.5	1.96	4.33	12.9	0.13	1.01	31.36	13.11	25.6	18.09	49.46	13.27	0.69
ica.oclstr.km.nc5.e4	8.03	1.02	2.8	6.14	21.53	0.96	1.01	31.04	18.28	30.23	29.41	60.45	1.63	0.69
ica.oclstr.km.nc5.e5	8.03	1.02	2.8	6.14	21.53	0.96	1.01	31.04	18.28	30.23	29.41	60.45	1.63	0.69
ica.oclstr.kh.nc1.e1	2.18	0.08	0.78	1.8	5.61	0.39	1	10.24	1.3	8.06	5.01	15.25	5.24	0.95
ica.oclstr.kh.nc1.e2	5.75	0.6	2.14	5.15	17.72	0.86	1	6.45	0.64	5.65	4.71	11.16	1.74	0.95
ica.oclstr.kh.nc1.e3	7.7	0.87	2.59	5.28	17.18	0.18	1.01	6.65	0.6	5.5	4.02	10.67	2.64	0.96
ica.oclstr.kh.nc1.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc1.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc2.e1	106.6	141.03	32.94	52.33	212.34	48.85	1.37	52.72	29.42	38.35	12.77	65.48	39.95	1.13
ica.oclstr.kh.nc2.e2	106.6	141.03	32.94	52.33	212.34	48.85	1.37	52.72	29.42	38.35	12.77	65.48	39.95	1.13
ica.oclstr.kh.nc2.e3	106.6	141.03	32.94	52.33	212.34	48.85	1.37	52.72	29.42	38.35	12.77	65.48	39.95	1.13
ica.oclstr.kh.nc2.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc2.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc3.e1	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc3.e2	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc3.e3	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc3.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc3.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc4.e1	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc4.e2	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc4.e3	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc4.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc4.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc5.e1	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61

Table A: continued

oclstr=ortho-clustering, kh=SOM clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)

nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error

rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
method of modeling	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
ica.oclstr.kh.nc5.e2	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc5.e3	90.82	157.96	34.86	86.88	246.41	6.72	0.75	39.31	16.31	28.55	9.24	48.55	30.07	0.61
ica.oclstr.kh.nc5.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.kh.nc5.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.at.nc5.e1	2.18	0.08	0.78	1.8	5.61	0.39	1	10.24	1.3	8.06	5.01	15.25	5.24	0.95
ica.oclstr.at.nc5.e2	5.75	0.6	2.14	5.15	17.72	0.86	1	6.45	0.64	5.65	4.71	11.16	1.74	0.95
ica.oclstr.at.nc5.e3	7.7	0.87	2.59	5.28	17.18	0.18	1.01	6.65	0.6	5.5	4.02	10.67	2.64	0.96
ica.oclstr.at.nc5.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.at.nc5.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.fa.nc5.e1	2.18	0.08	0.78	1.8	5.61	0.39	1	10.24	1.3	8.06	5.01	15.25	5.24	0.95
ica.oclstr.fa.nc5.e2	5.75	0.6	2.14	5.15	17.72	0.86	1	6.45	0.64	5.65	4.71	11.16	1.74	0.95
ica.oclstr.fa.nc5.e3	7.7	0.87	2.59	5.28	17.18	0.18	1.01	6.65	0.6	5.5	4.02	10.67	2.64	0.96
ica.oclstr.fa.nc5.e4	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.oclstr.fa.nc5.e5	11.19	1.97	3.89	8.47	25.37	0.82	1.02	4.39	0.26	3.61	2.6	6.99	1.79	1.03
ica.autregrma.v1.pol	5.54	0.41	1.65	3.22	12.25	0.64	0.98	6.68	0.47	4.84	1.5	8.18	5.18	1.07
ica.autregrma.v1.sin	5.17	0.34	1.68	2.7	9.82	1.08	0.98	2.17	0.06	1.76	1.22	3.4	0.95	0.98
ica.autregrma.v1.tnh	4.96	0.31	1.6	2.43	8.62	1.27	0.98	7.36	0.61	5.5	2.53	9.89	4.83	0.93
ica.autregrma.v1.exp	2.31	0.06	0.7	0.75	3.59	1.01	0.98	7.28	0.55	5.25	1.48	8.76	5.8	1.07
ica.autregrma.v2.pol	6.26	0.51	2.07	3.47	12.64	1.79	1.02	9.45	0.9	6.72	0.98	10.43	8.47	1.09
ica.autregrma.v2.sin	5.37	0.41	1.84	3.42	13.15	1.41	1.02	1.43	0.03	1.19	0.9	2.33	0.53	1.01
ica.autregrma.v2.tnh	4.89	0.36	1.72	3.42	13.32	1.04	1.02	4.26	0.25	3.54	2.63	6.89	1.63	0.96
ica.autregrma.v2.exp	2.57	0.09	0.88	1.65	5.16	0.05	1.01	5.29	0.35	4.15	2.55	7.85	2.74	1.05
ica.autregrma.v3.pol	2.37	0.06	0.69	0.3	2.8	1.74	0.98	5.25	0.35	4.18	2.7	7.96	2.55	1.05
ica.autregrma.v3.sin	2.37	0.06	0.7	0.45	2.95	1.38	0.98	2.52	0.07	1.82	0.5	3.02	2.02	0.99
ica.autregrma.v3.tnh	2.37	0.06	0.7	0.55	3.12	1.12	0.98	3.96	0.25	3.52	3.02	6.97	0.94	0.96
ica.autregrma.v3.exp	2.37	0.06	0.68	0.05	2.43	2.29	0.98	11.23	1.37	8.28	3.33	14.56	7.9	1.11
ica.autregrma.v4.pol	2.35	0.06	0.7	0.54	3.37	1.37	0.98	5.31	0.4	4.45	3.37	8.68	1.94	1.05
ica.autregrma.v4.sin	2.35	0.06	0.7	0.56	3.3	1.46	0.98	3.18	0.1	2.29	0.59	3.77	2.59	0.99
ica.autregrma.v4.tnh	2.35	0.06	0.7	0.6	3.29	1.51	0.98	4.13	0.31	3.92	3.69	7.82	0.44	0.96
ica.autregrma.v4.exp	2.35	0.06	0.7	0.56	3.53	1.24	0.98	11.43	1.39	8.32	2.81	14.24	8.62	1.11
ica.autregrma.v5.pol	0.26	0	0.09	0.15	0.65	0.04	1	7.81	0.69	5.86	2.77	10.58	5.04	1.08
ica.autregrma.v5.sin	0.39	0	0.13	0.24	1.02	0.02	1	2.58	0.1	2.27	1.91	4.5	0.67	1.02
ica.autregrma.v5.tnh	0.47	0	0.16	0.3	1.28	0.13	1	3.09	0.12	2.47	1.63	4.72	1.46	0.98
ica.autregrma.v5.exp	0.04	0	0.01	0.02	0.08	0	1	13.93	2.06	10.14	3.41	17.34	10.52	1.14

Table A: continued

oclstr=ortho-clustering, kh=SOM clustering,at=ART2, fa=fuzzy ART, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)

autregrma = ARMA, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic, exponential modeling functions

nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error

rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.simplregr.v1.pol	7.96	0.83	2.52	4.4	19.38	2.39	1.03	24.4	6.96	18.66	10.05	34.44	14.35	0.76
md.simplregr.v1.sin	7.61	0.9	2.62	5.62	19.24	0.72	1.03	16.78	2.84	11.91	1.43	18.21	15.35	1.01
md.simplregr.v1.tnh	7.97	1.05	2.84	6.45	19.5	0.03	1.03	17.55	4.26	14.59	10.85	28.4	6.7	1.11
md.simplregr.v1.exp	7.29	0.95	2.7	6.48	20.61	0.51	1.02	23.98	7.37	19.2	12.73	36.71	11.25	0.76
md.simplregr.v2.pol	8.09	0.89	2.62	4.85	20.44	1.95	1.04	23.37	6.5	18.03	10.21	33.58	13.16	0.77
md.simplregr.v2.sin	7.96	0.98	2.74	5.86	20.4	0.62	1.04	16.94	2.95	12.15	2.86	19.79	14.08	1.03
md.simplregr.v2.tnh	8.52	1.15	2.97	6.49	20.72	0.4	1.04	17.68	4.66	15.26	12.37	30.05	5.31	1.12
md.simplregr.v2.exp	7.49	1.02	2.8	6.75	21.82	0.15	1.03	22.93	6.94	18.63	12.97	35.9	9.97	0.77
md.simplregr.v3.pol	3.02	0.12	0.97	1.77	6.27	0.12	0.98	19.11	5.68	16.86	14.26	33.37	4.84	1.19
md.simplregr.v3.sin	2.78	0.12	0.95	2.01	6.38	0.26	0.98	30.49	16.57	28.78	25.97	57.45	3.52	1.3
md.simplregr.v3.tnh	3.71	0.17	1.15	1.87	7.6	0.54	0.98	31.73	18.04	30.03	23.17	59.96	3.62	1.23
md.simplregr.v3.exp	2.38	0.08	0.77	1.45	4.6	0.17	0.98	17.13	5.26	16.21	15.24	32.37	1.89	0.85
md.simplregr.v4.pol	3.15	0.13	0.99	1.67	6.15	0.53	0.98	19.41	5.97	17.27	14.84	34.24	4.57	1.19
md.simplregr.v4.sin	2.8	0.12	0.97	2.08	6.49	0.16	0.98	31.06	17.41	29.5	27.86	58.92	3.21	1.31
md.simplregr.v4.tnh	3.64	0.17	1.16	2.04	8.26	0.44	0.98	32.79	18.98	30.81	28.69	61.48	4.1	1.29
md.simplregr.v4.exp	2.41	0.08	0.79	1.53	4.61	0.04	0.98	17.78	5.65	16.8	15.77	33.55	2.01	0.84
md.simplregr.v5.pol	2.2	0.07	0.75	1.58	6.17	0.14	1	21.99	6.97	18.67	14.61	36.6	7.38	1.22
md.simplregr.v5.sin	2.19	0.07	0.73	1.47	4.99	0.23	1	33.65	18.96	30.79	27.63	61.28	6.03	1.34
md.simplregr.v5.tnh	2.88	0.13	1.01	2.19	6.53	0.02	1	32.56	20.38	31.92	31.28	63.84	1.28	1.31
md.simplregr.v5.exp	1.35	0.02	0.44	0.81	2.78	0.24	1	17.55	4.82	15.52	13.18	30.73	4.36	0.87
md.cr.fc.v1.pol.nc2	4.31	0.29	1.5	3.25	9.49	0.17	1.02	13.19	1.97	9.93	4.79	17.99	8.4	1.05
md.cr.fc.v1.pol.nc3	1.96	0.06	0.66	1.35	4.83	0.21	1.02	32.34	12.24	24.74	13.36	45.7	18.98	1.32
md.cr.fc.v1.pol.nc4	1.94	0.05	0.64	1.22	4.83	0.38	1.02	15.53	2.46	11.08	2.09	17.62	13.44	0.98
md.cr.fc.v1.pol.nc5	1.93	0.05	0.62	1.12	4.83	0.56	1.02	15.45	2.43	11.03	2.17	17.62	13.28	0.98
md.cr.fc.v1.sin.nc2	3.3	0.18	1.17	2.62	3.11	0.04	1.02	7.08	0.6	5.46	3.07	10.16	4.01	1.07
md.cr.fc.v1.sin.nc3	2.04	0.06	0.69	1.42	4.93	0.27	1.02	27.36	7.53	19.41	2.22	29.58	25.14	1.27
md.cr.fc.v1.sin.nc4	1.97	0.05	0.65	1.26	4.93	0.34	1.02	17.29	3	12.24	0.73	18.02	16.56	1.01
md.cr.fc.v1.sin.nc5	1.96	0.05	0.64	1.21	4.93	0.34	1.02	16.78	2.82	11.87	0.22	17	16.56	1
md.cr.fc.v1.tnh.nc2	2.93	0.14	1.03	2.26	6.76	0.4	1.02	6.18	0.53	5.14	3.83	10.01	2.35	1.06
md.cr.fc.v1.tnh.nc3	2.11	0.07	0.71	1.46	4.99	0.47	1.02	25.3	6.48	18	2.76	28.06	22.54	1.25
md.cr.fc.v1.tnh.nc4	1.99	0.06	0.66	1.33	4.99	0.15	1.02	17.58	3.15	12.56	2.51	20.09	15.06	1.03
md.cr.fc.v1.tnh.nc5	1.99	0.06	0.66	1.28	4.99	0.15	1.02	23.96	6.53	18.08	8.9	32.86	15.06	1.09
md.cr.fc.v1.exp.nc2	1.62	0.03	0.49	0.76	2.74	0.27	1.02	10.72	1.38	8.3	4.78	15.5	5.94	1.11

Table B: performance statistics of all models on problem of estimation of life of converter lining (median R&D)

* simplregr = simple rigression, cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.cr.fc.v1.exp.nc3	1.58	0.03	0.45	0.38	2.3	1	1.02	20.72	6.34	17.81	14.32	35.04	6.4	1.21
md.cr.fc.v1.exp.nc4	1.57	0.03	0.44	0.32	2.3	1	1.02	13.52	1.85	9.63	1.6	15.12	11.93	1.14
md.cr.fc.v1.exp.nc5	1.58	0.03	0.45	0.36	2.3	1	1.02	9.72	1.19	7.71	4.94	14.67	4.78	1.1
md.cr.fc.v2.pol.nc2	4.74	0.35	1.65	3.57	10.41	0.43	1.03	12.95	2.31	10.76	7.99	20.94	4.96	1.08
md.cr.fc.v2.pol.nc3	3.12	0.12	0.97	1.56	6.1	0.15	1.03	34.74	14.06	26.52	14.11	48.86	20.63	1.35
md.cr.fc.v2.pol.nc4	3.1	0.12	0.95	1.45	6.1	0.15	1.03	15.8	2.5	11.17	0.34	16.14	15.46	1
md.cr.fc.v2.pol.nc5	3.09	0.11	0.94	1.37	6.1	0.15	1.03	15.66	2.46	11.08	0.48	16.14	15.19	1
md.cr.fc.v2.sin.nc2	4.01	0.24	1.36	2.86	9.09	0.7	1.03	10.4	1.14	7.56	2.48	12.88	7.93	1.1
md.cr.fc.v2.sin.nc3	3.14	0.13	0.99	1.68	6.2	0.05	1.03	29.62	8.84	21.02	2.58	32.2	27.04	1.3
md.cr.fc.v2.sin.nc4	3.12	0.12	0.96	1.5	6.2	0.05	1.03	17.75	3.22	12.68	2.53	20.29	15.22	1.03
md.cr.fc.v2.sin.nc5	3.11	0.12	0.95	1.46	6.2	0.05	1.03	17.24	3.01	12.27	2.01	19.25	15.22	1.02
md.cr.fc.v2.tnh.nc2	3.68	0.2	1.25	2.61	8.03	0.69	1.03	9.16	0.95	6.89	3.32	12.48	5.83	1.09
md.cr.fc.v2.tnh.nc3	3.16	0.13	1	1.78	6.26	0	1.03	27.52	7.64	19.55	2.61	30.13	24.92	1.28
md.cr.fc.v2.tnh.nc4	3.13	0.12	0.97	1.57	6.26	0	1.03	18.14	3.48	13.19	4.36	22.5	13.78	1.04
md.cr.fc.v2.tnh.nc5	3.12	0.12	0.96	1.53	6.26	0	1.03	25.6	7.95	19.94	11.82	37.41	13.78	1.12
md.cr.fc.v2.exp.nc2	2.98	0.1	0.86	0.78	4.12	1.52	1.03	12	1.65	9.09	4.62	16.62	7.38	1.12
md.cr.fc.v2.exp.nc3	2.95	0.09	0.82	0.38	3.64	2.37	1.03	22.15	7.37	19.2	15.7	37.86	6.45	1.22
md.cr.fc.v2.exp.nc4	2.93	0.09	0.82	0.32	3.64	2.37	1.03	16.73	2.93	12.11	3.65	20.38	13.09	1.17
md.cr.fc.v2.exp.nc5	2.95	0.09	0.82	0.36	3.64	2.37	1.03	12.08	1.82	9.55	6.03	18.11	6.05	1.12
md.cr.fc.v3.pol.nc2	2.36	0.06	0.66	0.24	2.78	1.77	0.98	11.33	1.33	8.16	2.16	13.49	9.18	0.98
md.cr.fc.v3.pol.nc3	2.36	0.06	0.66	0.19	2.77	1.98	0.98	11.08	1.33	8.16	3.21	14.29	7.87	1.11
md.cr.fc.v3.pol.nc4	2.37	0.06	0.66	0.12	2.62	2.14	0.98	11.68	2.51	11.2	10.69	22.37	0.99	0.88
md.cr.fc.v3.pol.nc5	2.37	0.06	0.66	0.11	2.62	2.14	0.98	13.44	2.6	11.41	8.93	22.37	4.51	0.91
md.cr.fc.v3.sin.nc2	2.35	0.06	0.66	0.29	2.78	1.67	0.98	17.39	3.1	12.46	2.8	20.19	14.6	0.97
md.cr.fc.v3.sin.nc3	2.36	0.06	0.66	0.25	2.89	1.84	0.98	10.98	1.66	9.11	6.73	17.71	4.25	1.07
md.cr.fc.v3.sin.nc4	2.36	0.06	0.66	0.15	2.7	2.07	0.98	12.78	2.51	11.21	9.37	22.16	3.41	0.91
md.cr.fc.v3.sin.nc5	2.36	0.06	0.66	0.15	2.7	2.07	0.98	13.85	2.61	11.42	8.3	22.16	5.55	0.92
md.cr.fc.v3.tnh.nc2	2.35	0.06	0.66	0.34	2.8	1.55	0.98	20.55	4.28	14.63	2.33	22.89	18.22	0.98
md.cr.fc.v3.tnh.nc3	2.35	0.06	0.66	0.29	2.96	1.77	0.98	12.71	1.89	9.73	5.28	17.99	7.43	1.05
md.cr.fc.v3.tnh.nc4	2.36	0.06	0.66	0.18	2.75	2.01	0.98	12.87	2.38	10.9	8.48	21.35	4.4	0.92
md.cr.fc.v3.tnh.nc5	2.36	0.06	0.66	0.18	2.75	2.01	0.98	16.61	2.98	12.21	4.74	21.35	11.87	0.83
md.cr.fc.v3.exp.nc2	2.36	0.06	0.66	0.35	3.01	1.67	0.98	5.72	0.4	4.49	2.75	8.47	2.97	1.06
md.cr.fc.v3.exp.nc3	2.36	0.06	0.66	0.06	2.48	2.26	0.98	18.65	4.84	15.56	11.67	30.32	6.98	1.19

Table B: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.cr.fc.v3.exp.nc4	2.37	0.06	0.66	0.04	2.45	2.29	0.98	7.73	0.6	5.48	0.44	8.17	7.3	1
md.cr.fc.v3.exp.nc5	2.37	0.06	0.66	0.04	2.44	2.28	0.98	5.08	0.41	4.54	3.94	9.02	1.14	0.96
md.cr.fc.v4.pol.nc2	2.43	0.06	0.68	0.34	3.01	1.69	0.98	11.76	1.44	8.48	2.35	14.11	9.41	0.98
md.cr.fc.v4.pol.nc3	2.43	0.06	0.68	0.32	3.08	1.77	0.98	11.25	1.38	8.3	3.34	14.59	7.91	1.11
md.cr.fc.v4.pol.nc4	2.43	0.06	0.68	0.32	3.08	1.77	0.98	12.09	2.67	11.55	10.98	23.06	1.11	0.88
md.cr.fc.v4.pol.nc5	2.43	0.06	0.68	0.31	3.08	1.77	0.98	13.76	2.76	11.75	9.3	23.06	4.46	0.91
md.cr.fc.v4.sin.nc2	2.42	0.06	0.68	0.32	3.01	1.74	0.98	17.97	3.32	12.88	3	20.97	14.96	0.97
md.cr.fc.v4.sin.nc3	2.42	0.06	0.68	0.31	3.02	1.82	0.98	11.3	1.74	9.33	6.8	18.1	4.5	1.07
md.cr.fc.v4.sin.nc4	2.43	0.06	0.68	0.29	3.02	1.82	0.98	13.12	2.67	11.55	9.72	22.84	3.4	0.9
md.cr.fc.v4.sin.nc5	2.43	0.06	0.68	0.28	3.02	1.82	0.98	14.19	2.76	11.75	8.66	22.84	5.53	0.91
md.cr.fc.v4.tnh.nc2	2.42	0.06	0.68	0.32	3.04	1.77	0.98	21.21	4.56	15.1	2.53	23.73	18.68	0.97
md.cr.fc.v4.tnh.nc3	2.42	0.06	0.68	0.3	2.98	1.86	0.98	13.08	1.99	9.98	5.32	18.39	7.76	1.05
md.cr.fc.v4.tnh.nc4	2.42	0.06	0.68	0.27	2.98	1.86	0.98	13.22	2.52	11.23	8.8	22.02	4.42	0.91
md.cr.fc.v4.tnh.nc5	2.42	0.06	0.68	0.27	2.98	1.86	0.98	17.08	3.16	12.57	4.94	22.02	12.15	0.83
md.cr.fc.v4.exp.nc2	2.43	0.06	0.69	0.43	3.12	1.67	0.98	5.7	0.39	4.42	2.59	8.28	3.11	1.06
md.cr.fc.v4.exp.nc3	2.43	0.06	0.68	0.36	3.14	1.71	0.98	19.01	5.03	15.86	11.9	30.91	7.11	1.19
md.cr.fc.v4.exp.nc4	2.42	0.06	0.68	0.33	3.14	1.71	0.98	7.89	0.62	5.58	0.27	8.16	7.63	1
md.cr.fc.v4.exp.nc5	2.44	0.06	0.68	0.39	3.14	1.71	0.98	5.35	0.46	4.8	4.17	9.52	1.18	0.96
md.cr.fc.v5.pol.nc2	0.18	0	0.07	0.17	0.62	0.01	1	11.61	1.35	8.21	0.22	11.82	11.39	1
md.cr.fc.v5.pol.nc3	0.15	0	0.06	0.13	0.42	0.01	1	13.77	2	10.01	3.29	17.06	10.48	1.14
md.cr.fc.v5.pol.nc4	0.09	0	0.03	0.07	0.26	0.01	1	10.95	2.11	10.27	9.54	20.49	1.41	0.9
md.cr.fc.v5.pol.nc5	0.08	0	0.03	0.08	0.26	0.01	1	13.77	2.35	10.83	6.72	20.49	7.04	0.93
md.cr.fc.v5.sin.nc2	0.22	0	0.08	0.2	0.72	0	1	17.82	3.18	12.6	0.44	18.25	17.38	1
md.cr.fc.v5.sin.nc3	0.19	0	0.07	0.17	0.54	0	1	11.25	2.13	10.33	9.32	20.57	1.93	1.09
md.cr.fc.v5.sin.nc4	0.12	0	0.04	0.1	0.34	0.01	1	13.09	2.23	10.56	7.17	20.27	5.92	0.93
md.cr.fc.v5.sin.nc5	0.11	0	0.04	0.1	0.34	0.01	1	14.19	2.38	10.92	6.08	20.27	8.11	0.94
md.cr.fc.v5.tnh.nc2	0.26	0	0.1	0.24	0.83	0.01	1	21.05	4.43	14.89	0.04	21.09	21.02	1
md.cr.fc.v5.tnh.nc3	0.23	0	0.08	0.19	0.62	0.01	1	13.02	2.31	10.74	7.84	20.86	5.18	1.08
md.cr.fc.v5.tnh.nc4	0.14	0	0.05	0.12	0.4	0.01	1	13.19	2.13	10.32	6.26	19.44	6.93	0.94
md.cr.fc.v5.tnh.nc5	0.13	0	0.05	0.12	0.4	0.02	1	14.59	2.36	10.87	4.86	19.44	9.73	0.85
md.cr.fc.v5.exp.nc2	0.27	0	0.1	0.24	0.71	0.01	1	8.29	0.77	6.19	2.82	11.1	5.47	1.08
md.cr.fc.v5.exp.nc3	0.04	0	0.02	0.04	0.11	0.01	1	21.53	6.06	17.41	11.96	33.49	9.57	1.22
md.cr.fc.v5.exp.nc4	0.03	0	0.01	0.03	0.09	0	1	7.92	0.71	5.96	2.87	10.79	5.05	1.03

Table B: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.cr.fc.v5.exp.nc5	0.03	0	0.01	0.02	0.09	0	1	5.2	0.3	3.85	1.61	6.81	3.59	0.98
md.cr.km.v1.pol.nc2	3.29	0.18	1.19	2.75	10.25	0.26	1.02	1.04	0.02	0.89	0.72	1.76	0.32	1.01
md.cr.km.v1.pol.nc3	2.02	0.06	0.71	1.54	4.83	0.03	1.02	48.14	35.21	41.96	34.7	82.84	13.44	1.48
md.cr.km.v1.pol.nc4	2.12	0.07	0.73	1.53	6.22	0.56	1.02	15.45	2.43	11.03	2.17	17.62	13.28	0.98
md.cr.km.v1.pol.nc5	1.91	0.05	0.61	1.06	4.83	0.56	1.02	18.92	3.6	13.41	1.3	20.22	17.62	1.01
md.cr.km.v1.sin.nc2	2.86	0.16	1.11	2.78	10.46	0.21	1.02	10.65	1.31	8.1	4.23	14.88	6.42	1.11
md.cr.km.v1.sin.nc3	2.42	0.08	0.8	1.6	6.07	0.47	1.02	44.38	26.65	36.5	26.36	70.74	18.02	1.44
md.cr.km.v1.sin.nc4	2.11	0.07	0.72	1.5	5.98	0.34	1.02	16.78	2.82	11.87	0.22	17	16.56	1
md.cr.km.v1.sin.nc5	1.96	0.05	0.64	1.21	4.93	0.34	1.02	16.78	2.82	11.87	0.22	17	16.56	1
md.cr.km.v1.tnh.nc2	2.67	0.14	1.05	2.67	9.93	0.12	1.02	15.45	2.76	11.75	6.12	21.57	9.33	1.15
md.cr.km.v1.tnh.nc3	2.55	0.09	0.84	1.65	6.36	0.44	1.02	39.41	19.26	31.03	19.32	58.72	20.09	1.39
md.cr.km.v1.tnh.nc4	2.1	0.07	0.72	1.52	5.87	0.15	1.02	16.16	2.62	11.45	1.1	17.26	15.06	1.01
md.cr.km.v1.tnh.nc5	1.99	0.06	0.66	1.28	4.99	0.15	1.02	16.16	2.62	11.45	1.1	17.26	15.06	1.01
md.cr.km.v1.exp.nc2	1.62	0.03	0.49	0.76	2.74	0.27	1.02	10.72	1.38	8.3	4.78	15.5	5.94	1.11
md.cr.km.v1.exp.nc3	1.58	0.03	0.45	0.38	2.3	1	1.02	18.79	6.53	18.06	17.3	36.09	1.49	1.17
md.cr.km.v1.exp.nc4	1.59	0.03	0.46	0.47	2.74	0.75	1.02	12.18	1.57	8.86	2.94	15.12	9.25	1.12
md.cr.km.v1.exp.nc5	1.57	0.03	0.45	0.34	2.3	1	1.02	37.94	21.22	32.57	26.12	64.06	11.81	1.38
md.cr.km.v2.pol.nc2	3.99	0.25	1.4	3.09	11.69	0.18	1.03	1.84	0.03	1.3	0.09	1.93	1.74	1.02
md.cr.km.v2.pol.nc3	3.13	0.13	1	1.77	6.1	0.15	1.03	51.06	38.74	44.01	35.6	86.65	15.46	1.51
md.cr.km.v2.pol.nc4	3.26	0.13	1.01	1.67	7.47	0.67	1.03	15.66	2.46	11.08	0.48	16.14	15.19	1
md.cr.km.v2.pol.nc5	3.07	0.11	0.93	1.32	6.1	0.15	1.03	19.4	3.87	13.91	3.26	22.66	16.14	1.03
md.cr.km.v2.sin.nc2	3.59	0.23	1.33	3.16	11.83	0.15	1.03	12.14	1.6	8.93	3.51	15.65	8.62	1.12
md.cr.km.v2.sin.nc3	3.19	0.15	1.07	2.15	7.27	0.05	1.03	47.25	29.6	38.47	26.96	74.21	20.29	1.47
md.cr.km.v2.sin.nc4	3.24	0.13	1.01	1.66	7.24	0.56	1.03	17.24	3.01	12.27	2.01	19.25	15.22	1.02
md.cr.km.v2.sin.nc5	3.11	0.12	0.95	1.46	6.2	0.05	1.03	17.24	3.01	12.27	2.01	19.25	15.22	1.02
md.cr.km.v2.tnh.nc2	3.45	0.21	1.28	3.04	11.29	0.29	1.03	17.07	3.23	12.71	5.61	22.68	11.46	1.17
md.cr.km.v2.tnh.nc3	3.26	0.16	1.1	2.24	7.57	0	1.03	42.15	21.63	32.89	19.65	61.81	22.5	1.42
md.cr.km.v2.tnh.nc4	3.24	0.13	1.01	1.68	7.13	0.5	1.03	16.69	2.87	11.98	2.91	19.6	13.78	1.03
md.cr.km.v2.tnh.nc5	3.12	0.12	0.96	1.53	6.26	0	1.03	16.69	2.87	11.98	2.91	19.6	13.78	1.03
md.cr.km.v2.exp.nc2	2.98	0.1	0.86	0.78	4.12	1.52	1.03	12	1.65	9.09	4.62	16.62	7.38	1.12
md.cr.km.v2.exp.nc3	2.95	0.09	0.82	0.38	3.64	2.37	1.03	19.69	7.5	19.37	19.04	38.73	0.65	1.19
md.cr.km.v2.exp.nc4	2.96	0.09	0.83	0.46	4.07	2.11	1.03	15.08	2.56	11.3	5.3	20.38	9.79	1.15
md.cr.km.v2.exp.nc5	2.94	0.09	0.82	0.34	3.64	2.37	1.03	39	21.62	32.88	25.31	64.31	13.68	1.39

Table B: continued

cr = cluster wise regression, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.cr.km.v3.pol.nc2	2.36	0.06	0.66	0.33	3.26	1.64	0.98	8.16	0.89	6.68	4.77	12.93	3.39	1.08
md.cr.km.v3.pol.nc3	2.36	0.06	0.66	0.18	2.77	1.98	0.98	7.15	0.89	6.67	6.16	13.3	0.99	1.06
md.cr.km.v3.pol.nc4	2.37	0.06	0.66	0.13	2.62	2.14	0.98	13.44	2.6	11.41	8.93	22.37	4.51	0.91
md.cr.km.v3.pol.nc5	2.37	0.06	0.66	0.1	2.62	2.14	0.98	13.19	2.58	11.36	9.18	22.37	4.02	0.91
md.cr.km.v3.sin.nc2	2.35	0.06	0.66	0.35	3.28	1.58	0.98	15.64	2.55	11.29	3.16	18.81	12.48	1.16
md.cr.km.v3.sin.nc3	2.36	0.06	0.66	0.23	2.89	1.85	0.98	2.06	0.06	1.74	1.35	3.41	0.72	1.02
md.cr.km.v3.sin.nc4	2.36	0.06	0.66	0.17	2.7	2.07	0.98	13.85	2.61	11.42	8.3	22.16	5.55	0.92
md.cr.km.v3.sin.nc5	2.36	0.06	0.66	0.15	2.7	2.07	0.98	13.85	2.61	11.42	8.3	22.16	5.55	0.92
md.cr.km.v3.tnh.nc2	2.35	0.06	0.66	0.38	3.34	1.53	0.98	18.78	3.54	13.3	1.04	19.82	17.75	1.19
md.cr.km.v3.tnh.nc3	2.35	0.06	0.66	0.27	2.96	1.78	0.98	3.61	0.14	2.61	0.79	4.4	2.82	1.01
md.cr.km.v3.tnh.nc4	2.36	0.06	0.66	0.2	2.75	2.01	0.98	13.43	2.43	11.02	7.92	21.35	5.5	0.92
md.cr.km.v3.tnh.nc5	2.36	0.06	0.66	0.18	2.75	2.01	0.98	13.43	2.43	11.02	7.92	21.35	5.5	0.92
md.cr.km.v3.exp.nc2	2.36	0.06	0.66	0.35	3.01	1.67	0.98	5.72	0.4	4.49	2.75	8.47	2.97	1.06
md.cr.km.v3.exp.nc3	2.36	0.06	0.66	0.05	2.48	2.26	0.98	17.93	5.2	16.12	14.08	32.02	3.85	1.14
md.cr.km.v3.exp.nc4	2.37	0.06	0.66	0.04	2.45	2.29	0.98	8.18	0.68	5.82	0.88	9.07	7.3	1.01
md.cr.km.v3.exp.nc5	2.37	0.06	0.66	0.05	2.49	2.26	0.98	33.04	19.5	31.23	29.3	62.34	3.74	1.33
md.cr.km.v4.pol.nc2	2.43	0.06	0.68	0.43	3.09	1.72	0.98	8.17	0.88	6.65	4.66	12.83	3.52	1.08
md.cr.km.v4.pol.nc3	2.43	0.06	0.68	0.31	3.08	1.77	0.98	7.29	0.91	6.75	6.18	13.46	1.11	1.06
md.cr.km.v4.pol.nc4	2.43	0.06	0.68	0.29	2.96	1.74	0.98	13.76	2.76	11.75	9.3	23.06	4.46	0.91
md.cr.km.v4.pol.nc5	2.42	0.06	0.68	0.29	3.08	1.77	0.98	13.48	2.74	11.7	9.58	23.06	3.9	0.9
md.cr.km.v4.sin.nc2	2.42	0.06	0.68	0.4	3.11	1.77	0.98	15.84	2.6	11.4	3.01	18.84	12.83	1.16
md.cr.km.v4.sin.nc3	2.42	0.06	0.68	0.3	3.02	1.82	0.98	1.99	0.06	1.73	1.42	3.4	0.57	1.02
md.cr.km.v4.sin.nc4	2.42	0.06	0.68	0.27	2.89	1.79	0.98	14.19	2.76	11.75	8.66	22.84	5.53	0.91
md.cr.km.v4.sin.nc5	2.43	0.06	0.68	0.28	3.02	1.82	0.98	14.19	2.76	11.75	8.66	22.84	5.53	0.91
md.cr.km.v4.tnh.nc2	2.42	0.06	0.68	0.39	3.18	1.81	0.98	19.05	3.64	13.48	0.83	19.88	18.22	1.19
md.cr.km.v4.tnh.nc3	2.42	0.06	0.68	0.29	2.98	1.86	0.98	3.73	0.14	2.68	0.68	4.42	3.05	1.01
md.cr.km.v4.tnh.nc4	2.42	0.06	0.67	0.25	2.84	1.83	0.98	13.75	2.57	11.35	8.27	22.02	5.48	0.92
md.cr.km.v4.tnh.nc5	2.42	0.06	0.68	0.27	2.98	1.86	0.98	13.75	2.57	11.35	8.27	22.02	5.48	0.92
md.cr.km.v4.exp.nc2	2.43	0.06	0.69	0.43	3.12	1.67	0.98	5.7	0.39	4.42	2.59	8.28	3.11	1.06
md.cr.km.v4.exp.nc3	2.43	0.06	0.68	0.36	3.14	1.71	0.98	18.33	5.4	16.44	14.3	32.63	4.03	1.14
md.cr.km.v4.exp.nc4	2.43	0.06	0.68	0.34	3.05	1.67	0.98	8.38	0.71	5.95	0.75	9.13	7.63	1.01
md.cr.km.v4.exp.nc5	2.42	0.06	0.68	0.33	3.14	1.71	0.98	33.29	19.93	31.57	29.75	63.04	3.54	1.33
md.cr.km.v5.pol.nc2	0.2	0	0.09	0.27	0.91	0	1	10.78	1.4	8.37	4.89	15.67	5.9	1.11

Table B: continued

cr = cluster wise regression, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.cr.km.v5.pol.nc3	0.13	0	0.05	0.12	0.41	0.02	1	8.73	1.3	8.06	7.32	16.05	1.41	1.09
md.cr.km.v5.pol.nc4	0.1	0	0.04	0.08	0.26	0.01	1	13.77	2.35	10.83	6.72	20.49	7.04	0.93
md.cr.km.v5.pol.nc5	0.07	0	0.03	0.08	0.26	0.01	1	13.51	2.31	10.75	6.97	20.49	6.54	0.93
md.cr.km.v5.sin.nc2	0.22	0	0.1	0.28	0.93	0	1	18.45	3.51	13.25	3.24	21.69	15.21	1.18
md.cr.km.v5.sin.nc3	0.17	0	0.07	0.16	0.54	0.03	1	4.54	0.23	3.35	1.38	5.92	3.16	1.05
md.cr.km.v5.sin.nc4	0.14	0	0.05	0.1	0.34	0.03	1	14.19	2.38	10.92	6.08	20.27	8.11	0.94
md.cr.km.v5.sin.nc5	0.11	0	0.04	0.1	0.34	0.01	1	14.19	2.38	10.92	6.08	20.27	8.11	0.94
md.cr.km.v5.tnh.nc2	0.25	0	0.11	0.3	1	0	1	21.66	4.7	15.34	1.06	22.72	20.6	1.22
md.cr.km.v5.tnh.nc3	0.2	0	0.08	0.19	0.61	0.01	1	3.7	0.24	3.47	3.23	6.93	0.47	1.03
md.cr.km.v5.tnh.nc4	0.17	0	0.06	0.12	0.4	0.02	1	13.75	2.21	10.52	5.69	19.44	8.06	0.94
md.cr.km.v5.tnh.nc5	0.13	0	0.05	0.12	0.4	0.02	1	13.75	2.21	10.52	5.69	19.44	8.06	0.94
md.cr.km.v5.exp.nc2	0.27	0	0.1	0.24	0.71	0.01	1	8.29	0.77	6.19	2.82	11.1	5.47	1.08
md.cr.km.v5.exp.nc3	0.04	0	0.01	0.03	0.11	0	1	18.37	6.21	17.63	16.85	35.22	1.52	1.17
md.cr.km.v5.exp.nc4	0.03	0	0.01	0.03	0.09	0	1	8.38	0.81	6.38	3.33	11.71	5.05	1.03
md.cr.km.v5.exp.nc5	0.03	0	0.01	0.04	0.12	0	1	36.27	22.16	33.29	30.01	66.28	6.26	1.36
md.cr.kh.v1.pol.nc2	5.1	0.43	1.81	4.09	14.44	1.1	1.02	37.67	22.9	33.84	29.51	67.18	8.16	1.3
md.cr.kh.v1.pol.nc3	3.34	0.2	1.25	3.03	9.95	0.08	1.02	15.85	2.53	11.26	1.54	17.38	14.31	0.84
md.cr.kh.v1.pol.nc4	3.77	0.25	1.38	3.25	11.74	0.09	1.02	11.06	2.35	10.83	10.6	21.66	0.47	1.11
md.cr.kh.v1.pol.nc5	1.69	0.04	0.58	1.25	4.05	0.09	1.02	35.53	17.85	29.87	22.86	58.39	12.67	1.23
md.cr.kh.v1.sin.nc2	4.92	0.4	1.75	3.96	14.68	0.61	1.02	45.17	37.25	43.16	41.05	86.22	4.12	0.59
md.cr.kh.v1.sin.nc3	2.54	0.12	0.95	2.31	8.67	0.28	1.02	12.84	1.89	9.73	4.96	17.8	7.87	0.87
md.cr.kh.v1.sin.nc4	3.28	0.19	1.21	2.86	10.28	0.04	1.02	17.8	5.03	15.86	13.64	31.45	4.16	1.14
md.cr.kh.v1.sin.nc5	1.79	0.05	0.61	1.28	4.41	0.06	1.02	30.2	12.3	24.8	17.84	48.03	12.36	1.18
md.cr.kh.v1.tnh.nc2	4.68	0.36	1.66	3.71	13.47	0.5	1.02	49.24	48.18	49.08	48.92	98.16	0.32	0.51
md.cr.kh.v1.tnh.nc3	2.5	0.11	0.94	2.27	7.99	0.08	1.02	14.7	2.28	10.68	3.48	18.17	11.22	0.85
md.cr.kh.v1.tnh.nc4	3.1	0.17	1.13	2.65	9.68	0.03	1.02	20	5.92	17.2	13.85	33.85	6.16	1.2
md.cr.kh.v1.tnh.nc5	1.8	0.05	0.61	1.26	4.44	0.03	1.02	27.53	10.16	22.54	16.06	43.59	11.48	1.16
md.cr.kh.v1.exp.nc2	2.33	0.08	0.78	1.58	6.45	0.12	1.02	29.72	9.37	21.64	7.32	37.04	22.39	0.93
md.cr.kh.v1.exp.nc3	2.33	0.08	0.79	1.64	6.66	0.03	1.02	15.07	2.3	10.73	1.69	16.76	13.38	1.02
md.cr.kh.v1.exp.nc4	1.64	0.04	0.52	0.91	3.47	0.05	1.02	8.8	0.84	6.5	2.62	11.43	6.18	1.09
md.cr.kh.v1.exp.nc5	1.61	0.03	0.49	0.73	3.3	0.5	1.02	21.52	4.86	15.58	4.76	26.28	16.76	1.22
md.cr.kh.v2.pol.nc2	5.39	0.5	1.96	4.57	15.7	0.07	1.04	39.32	25.21	35.5	31.22	70.54	8.1	1.31
md.cr.kh.v2.pol.nc3	4.09	0.28	1.46	3.29	11.17	0.19	1.03	15.03	2.27	10.67	1.27	16.3	13.76	0.85

Table B: continued

cr = cluster wise regression, km=k-means clustering,kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modelling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.cr.kh.v2.pol.nc4	4.5	0.32	1.58	3.48	13.23	1.15	1.04	14.65	2.97	12.18	9.06	23.71	5.59	1.15
md.cr.kh.v2.pol.nc5	2.98	0.11	0.9	1.3	5.37	0.93	1.03	37.91	21.03	32.43	25.81	63.72	12.1	1.26
md.cr.kh.v2.sin.nc2	5.43	0.48	1.91	4.25	16.06	0.78	1.04	46.04	37.76	43.45	40.7	86.74	5.34	0.59
md.cr.kh.v2.sin.nc3	3.67	0.18	1.19	2.24	9.91	1.64	1.03	11.66	1.65	9.08	5.37	17.03	6.28	0.88
md.cr.kh.v2.sin.nc4	4	0.26	1.42	3.19	11.7	0.24	1.03	17.37	5.76	16.97	16.57	33.93	0.8	1.17
md.cr.kh.v2.sin.nc5	2.98	0.11	0.92	1.44	5.72	0.42	1.03	32.14	14.49	26.91	20.39	52.53	11.75	1.2
md.cr.kh.v2.tnh.nc2	5.17	0.43	1.82	4.06	14.88	0.55	1.04	49.77	48.65	49.32	48.86	93.64	0.91	0.51
md.cr.kh.v2.tnh.nc3	3.63	0.18	1.18	2.23	9.25	1.47	1.03	13.42	1.94	9.84	3.68	17.1	9.75	0.87
md.cr.kh.v2.tnh.nc4	3.82	0.24	1.35	3.03	11.09	0.05	1.03	22.11	6.91	18.58	14.2	36.31	7.91	1.22
md.cr.kh.v2.tnh.nc5	2.98	0.11	0.92	1.45	5.76	0.3	1.03	29.25	11.97	24.46	18.46	47.71	10.79	1.18
md.cr.kh.v2.exp.nc2	3.48	0.15	1.06	1.59	7.85	1.25	1.03	30.23	9.45	21.73	5.54	35.77	24.7	0.94
md.cr.kh.v2.exp.nc3	3.5	0.15	1.07	1.63	8.1	1.35	1.03	15.63	2.56	11.32	3.5	19.13	12.13	1.03
md.cr.kh.v2.exp.nc4	3	0.1	0.87	0.91	4.89	1.42	1.03	10.19	1.11	7.45	2.67	12.86	7.52	1.1
md.cr.kh.v2.exp.nc5	2.97	0.09	0.85	0.74	4.67	1.85	1.03	23.78	5.95	17.24	5.42	29.2	18.35	1.24
md.cr.kh.v3.pol.nc2	2.81	0.09	0.85	1.25	6.35	1.25	0.98	24	7.43	19.27	12.92	36.92	11.09	1.13
md.cr.kh.v3.pol.nc3	2.31	0.06	0.7	0.99	4.84	0.02	0.98	17.24	3	12.25	1.69	18.93	15.55	0.83
md.cr.kh.v3.pol.nc4	2.46	0.07	0.73	0.95	5.25	1	0.98	28.18	11.1	23.56	17.77	45.95	10.42	0.82
md.cr.kh.v3.pol.nc5	2.38	0.06	0.66	0.16	2.7	2.09	0.98	9.3	0.9	6.7	1.84	11.14	7.46	1.02
md.cr.kh.v3.sin.nc2	2.83	0.1	0.86	1.23	6.36	1.23	0.98	27.94	8.57	20.71	8.78	36.71	19.16	0.72
md.cr.kh.v3.sin.nc3	2.36	0.06	0.66	0.18	2.71	1.92	0.98	22.68	5.2	16.13	2.4	25.08	20.29	0.77
md.cr.kh.v3.sin.nc4	2.39	0.07	0.71	0.91	4.81	0.54	0.98	36	16.46	28.69	18.71	54.71	17.28	0.81
md.cr.kh.v3.sin.nc5	2.38	0.06	0.66	0.17	2.75	2.07	0.98	9.79	1	7.07	2.04	11.83	7.75	1.02
md.cr.kh.v3.tnh.nc2	2.85	0.1	0.86	1.24	6.4	1.25	0.98	42.21	22.33	33.41	21.25	63.46	20.96	0.58
md.cr.kh.v3.tnh.nc3	2.34	0.06	0.66	0.3	2.86	1.72	0.98	24.83	6.42	17.91	5.02	29.85	19.8	0.75
md.cr.kh.v3.tnh.nc4	2.35	0.06	0.7	0.93	4.68	0.32	0.98	11.08	2.44	11.04	11	22.07	0.08	1.11
md.cr.kh.v3.tnh.nc5	2.38	0.06	0.66	0.16	2.74	2.1	0.98	9.96	1.04	7.21	2.22	12.17	7.74	1.02
md.cr.kh.v3.exp.nc2	2.49	0.09	0.83	1.65	7.62	1.04	0.98	26.81	8.79	20.96	12.63	39.45	14.18	0.87
md.cr.kh.v3.exp.nc3	2.53	0.09	0.84	1.66	7.78	1.09	0.98	12.19	1.63	9.03	3.81	16	8.38	0.96
md.cr.kh.v3.exp.nc4	2.34	0.06	0.67	0.58	3.44	0.82	0.98	5.29	0.31	3.92	1.66	6.96	3.63	1.05
md.cr.kh.v3.exp.nc5	2.34	0.06	0.67	0.55	3.37	0.95	0.98	14	2.04	10.11	2.87	16.87	11.13	1.14
md.cr.kh.v4.pol.nc2	2.83	0.09	0.85	1.14	6.2	1.55	0.98	24.3	7.61	19.51	13.05	37.35	11.26	1.13
md.cr.kh.v4.pol.nc3	2.38	0.07	0.71	0.92	4.76	0.5	0.98	17.69	3.15	12.55	1.37	19.06	16.33	0.82
md.cr.kh.v4.pol.nc4	2.47	0.07	0.74	1.02	5.11	0.6	0.98	29.13	11.87	24.36	18.4	47.53	10.74	0.82

Table B: continued

cr = cluster wise regression,kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slop
md.cr.kh.v4.pol.nc5	2.41	0.06	0.67	0.26	2.77	1.79	0.98	9.18	0.87	6.6	1.66	10.84	7.52	1.02
md.cr.kh.v4.sin.nc2	2.86	0.09	0.85	1.1	6.16	1.46	0.98	28.67	8.99	21.2	8.77	37.44	19.9	0.71
md.cr.kh.v4.sin.nc3	2.4	0.06	0.67	0.17	2.63	1.99	0.98	23.23	5.48	16.55	2.86	26.09	20.37	0.77
md.cr.kh.v4.sin.nc4	2.39	0.07	0.72	0.97	4.66	0.13	0.98	37.14	17.54	29.61	19.36	56.5	17.77	0.81
md.cr.kh.v4.sin.nc5	2.41	0.06	0.67	0.27	2.79	1.76	0.98	9.69	0.97	6.98	1.87	11.56	7.82	1.02
md.cr.kh.v4.tnh.nc2	2.88	0.09	0.85	1.11	6.21	1.48	0.98	43.29	23.38	34.19	21.55	64.83	21.74	0.57
md.cr.kh.v4.tnh.nc3	2.4	0.06	0.67	0.21	2.8	2.02	0.98	25.44	6.78	18.41	5.53	30.97	19.91	0.75
md.cr.kh.v4.tnh.nc4	2.37	0.07	0.71	0.94	4.53	0.1	0.98	11.4	2.57	11.34	11.28	22.68	0.12	1.11
md.cr.kh.v4.tnh.nc5	2.41	0.06	0.67	0.26	2.78	1.79	0.98	9.86	1.01	7.12	2.05	11.91	7.81	1.02
md.cr.kh.v4.exp.nc2	2.49	0.09	0.82	1.61	7.56	0.72	0.98	27.24	9.13	21.36	13.07	40.3	14.17	0.87
md.cr.kh.v4.exp.nc3	2.52	0.09	0.83	1.64	7.77	0.82	0.98	12.12	1.62	9.01	3.94	16.05	8.18	0.96
md.cr.kh.v4.exp.nc4	2.39	0.06	0.68	0.51	3.24	1.35	0.98	5.35	0.31	3.97	1.67	7.02	3.69	1.05
md.cr.kh.v4.exp.nc5	2.38	0.06	0.67	0.42	3.26	1.52	0.98	14.03	2.04	10.09	2.63	16.66	11.39	1.14
md.cr.kh.v5.pol.nc2	1.27	0.05	0.61	1.78	6.35	0.06	1	24.58	8.49	20.61	15.65	40.24	8.93	1.16
md.cr.kh.v5.pol.nc3	0.62	0.01	0.28	0.82	2.53	0.01	1	15.23	2.35	10.84	1.73	16.96	13.5	0.85
md.cr.kh.v5.pol.nc4	0.75	0.02	0.36	1.08	3.45	0.01	1	28.87	10.82	23.26	15.77	44.64	13.09	0.84
md.cr.kh.v5.pol.nc5	0.12	0	0.05	0.11	0.34	0	1	9.52	1.09	7.39	4.31	13.83	5.21	1.04
md.cr.kh.v5.sin.nc2	1.19	0.05	0.61	1.86	6.53	0.02	1	26.19	7.67	19.58	8.99	35.18	17.2	0.74
md.cr.kh.v5.sin.nc3	0.13	0	0.05	0.13	0.46	0	1	20.81	4.39	14.82	2.46	23.27	18.35	0.79
md.cr.kh.v5.sin.nc4	0.68	0.01	0.31	0.9	2.98	0.05	1	36.87	16.4	28.63	16.74	53.61	20.13	0.83
md.cr.kh.v5.sin.nc5	0.13	0	0.05	0.12	0.39	0	1	10.03	1.21	7.78	4.52	14.55	5.51	1.05
md.cr.kh.v5.tnh.nc2	1.2	0.05	0.62	1.88	6.61	0	1	40.81	21.39	32.7	21.76	62.57	19.04	0.59
md.cr.kh.v5.tnh.nc3	0.22	0	0.08	0.21	0.66	0.02	1	23	5.56	16.67	5.14	28.15	17.86	0.77
md.cr.kh.v5.tnh.nc4	0.69	0.01	0.3	0.82	2.75	0.05	1	13.77	3.16	12.58	11.26	25.03	2.51	1.14
md.cr.kh.v5.tnh.nc5	0.12	0	0.05	0.12	0.38	0	1	10.2	1.26	7.94	4.69	14.89	5.51	1.05
md.cr.kh.v5.exp.nc2	1.38	0.04	0.57	1.51	5.38	0.17	1	27.46	8.65	20.79	10.52	37.98	16.95	0.89
md.cr.kh.v5.exp.nc3	1.33	0.04	0.58	1.62	5.54	0.02	1	12.48	1.58	8.89	1.47	13.96	11.01	0.99
md.cr.kh.v5.exp.nc4	0.38	0	0.16	0.46	1.59	0.01	1	7.85	0.64	5.68	1.71	9.55	6.14	1.08
md.cr.kh.v5.exp.nc5	0.37	0	0.16	0.43	1.46	0.01	1	16.76	2.9	12.04	2.94	19.71	13.82	1.17
md.cr.at.v1.pol.nc5	1.72	0.04	0.58	1.21	4.68	0.23	1.02	15.53	2.46	11.08	2.09	17.62	13.44	0.98
md.cr.at.v1.sin.nc5	4.1	0.25	1.4	2.93	9.3	0.58	1.02	24.6	6.05	17.4	0.54	25.14	24.06	1.25
md.cr.at.v1.tnh.nc5	4.06	0.25	1.37	2.84	9.24	0.47	1.02	25.31	6.48	18	2.75	28.06	22.56	1.25
md.cr.at.v1.exp.nc5	1.54	0.02	0.43	0.18	1.9	1.25	1.02	5.91	0.46	4.8	3.34	9.25	2.57	1.03

Table B: continued

cr = cluster wise regression, kh=SOM clustering, at=A.R.T.2 clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.cr.at.v2.pol.nc5	3.04	0.11	0.91	1.22	5.95	1.19	1.03	15.8	2.5	11.17	0.34	16.14	15.46	1
md.cr.at.v2.sin.nc5	4.78	0.32	1.57	3.06	10.47	1.5	1.03	28.5	8.14	20.18	1.46	29.96	27.04	1.28
md.cr.at.v2.tnh.nc5	4.75	0.31	1.56	2.99	10.38	1.87	1.03	29.12	8.49	20.6	1	30.13	28.12	1.29
md.cr.at.v2.exp.nc5	2.9	0.08	0.81	0.18	3.27	2.62	1.03	5.89	0.5	4.99	3.89	9.79	2	1.04
md.cr.at.v3.pol.nc5	2.37	0.06	0.66	0.11	2.62	2.14	0.98	11.68	2.51	11.2	10.69	22.37	0.99	0.88
md.cr.at.v3.sin.nc5	2.36	0.06	0.66	0.3	2.99	1.65	0.98	21.3	4.67	15.27	3.59	24.89	17.71	0.96
md.cr.at.v3.tnh.nc5	2.35	0.06	0.66	0.34	3.05	1.56	0.98	22.64	5.34	16.34	4.65	27.28	17.99	0.95
md.cr.at.v3.exp.nc5	2.37	0.06	0.66	0.01	2.39	2.34	0.98	5.6	0.43	4.66	3.47	9.07	2.13	1.03
md.cr.at.v4.pol.nc5	2.43	0.06	0.68	0.33	3.32	1.88	0.98	12.09	2.67	11.55	10.98	23.06	1.11	0.88
md.cr.at.v4.sin.nc5	2.42	0.06	0.68	0.31	2.84	1.77	0.98	21.94	4.96	15.75	3.84	25.78	18.1	0.96
md.cr.at.v4.tnh.nc5	2.42	0.06	0.68	0.31	2.81	1.8	0.98	23.31	5.68	16.85	4.92	28.23	18.39	0.95
md.cr.at.v4.exp.nc5	2.39	0.06	0.66	0.2	2.79	2.06	0.98	5.61	0.44	4.68	3.52	9.13	2.09	1.04
md.cr.at.v5.pol.nc5	0.09	0	0.03	0.08	0.26	0.01	1	10.95	2.11	10.27	9.54	20.49	1.41	0.9
md.cr.at.v5.sin.nc5	0.22	0	0.09	0.22	0.74	0	1	21.82	4.78	15.45	1.25	23.07	20.57	0.99
md.cr.at.v5.tnh.nc5	0.25	0	0.1	0.24	0.83	0.01	1	23.19	5.43	16.48	2.33	25.52	20.86	0.98
md.cr.at.v5.exp.nc5	0.01	0	0	0.01	0.03	0	1	5.98	0.69	5.86	5.73	11.71	0.24	1.06
md.cr.fa.v1.pol.nc5	4.09	0.28	1.46	3.31	10.76	0.17	1.02	52.82	50.16	50.08	47.18	100	5.63	0.47
md.cr.fa.v1.sin.nc5	2.76	0.14	1.02	2.43	8.37	0.03	1.02	68.7	56.99	53.38	31.3	100	37.39	0.69
md.cr.fa.v1.tnh.nc5	2.66	0.12	0.97	2.28	7.8	0.04	1.02	68.66	56.96	53.37	31.34	100	37.32	0.69
md.cr.fa.v1.exp.nc5	6.35	0.62	2.19	4.69	16.5	1.3	1.02	51.53	50.05	50.02	48.47	100	3.06	0.48
md.cr.fa.v2.pol.nc5	4.54	0.35	1.64	3.79	12.14	0.51	1.04	52.68	50.14	50.07	47.32	100	5.37	0.47
md.cr.fa.v2.sin.nc5	3.74	0.2	1.25	2.52	9.6	0.68	1.03	69.97	57.98	53.84	30.03	100	39.94	0.7
md.cr.fa.v2.tnh.nc5	3.66	0.19	1.21	2.39	9.04	0.74	1.03	69.94	57.95	53.83	30.06	100	39.88	0.7
md.cr.fa.v2.exp.nc5	6.54	0.72	2.35	5.38	17.94	0.48	1.04	51.02	50.02	50.01	48.98	100	2.04	0.49
md.cr.fa.v3.pol.nc5	2.44	0.07	0.73	0.93	5.22	0.98	0.98	52.16	50.09	50.05	47.84	100	4.33	0.52
md.cr.fa.v3.sin.nc5	2.34	0.06	0.65	0.29	2.73	1.85	0.98	62.98	53.37	51.66	37.02	100	25.95	0.63
md.cr.fa.v3.tnh.nc5	2.34	0.06	0.65	0.32	2.76	1.78	0.98	62.67	53.21	51.58	37.33	100	25.35	0.63
md.cr.fa.v3.exp.nc5	6.37	0.54	2.03	3.6	11.28	0.06	0.98	53.39	50.23	50.11	46.61	100	6.77	0.47
md.cr.fa.v4.pol.nc5	2.46	0.07	0.73	0.97	5.07	0.59	0.98	52.03	50.08	50.04	47.97	100	4.05	0.52
md.cr.fa.v4.sin.nc5	2.41	0.06	0.67	0.21	2.76	1.95	0.98	63.06	53.41	51.68	36.94	100	26.13	0.63
md.cr.fa.v4.tnh.nc5	2.4	0.06	0.67	0.21	2.78	1.99	0.98	62.76	53.25	51.6	37.24	100	25.51	0.63
md.cr.fa.v4.exp.nc5	6.36	0.53	2.02	3.57	11.29	0.42	0.98	53.66	50.27	50.13	46.34	100	7.33	0.46
md.cr.fa.v5.pol.nc5	0.76	0.02	0.36	1.05	3.43	0.1	1	53.43	50.23	50.12	46.57	100	6.86	0.53

Table B: continued

cr = cluster wise regression, at=A.R.T.2 clustering, fa= fuzzy ART, clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, md = data prepared using median with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modeling	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.oclstr.fc.nc1.e1	2.18	0.07	0.75	1.63	6.35	0.15	1	20.7	6.44	17.95	14.69	35.39	6.01	1.21
md.oclstr.fc.nc1.e2	2.24	0.08	0.78	1.67	6.35	0.22	1	19.22	5.98	17.29	15.12	34.34	4.1	1.19
md.oclstr.fc.nc1.e3	7.97	0.8	2.48	4.07	13.6	0.73	1.01	16.1	2.63	11.47	2.04	18.14	14.06	0.98
md.oclstr.fc.nc1.e4	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.fc.nc1.e5	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.fc.nc2.e1	1.36	0.03	0.5	1.19	3.68	0.04	1	5.67	0.53	5.15	4.57	10.24	1.09	1.06
md.oclstr.fc.nc2.e2	3.48	0.21	1.27	2.98	10.63	0.07	1	5.23	0.4	4.5	3.62	8.85	1.61	1.04
md.oclstr.fc.nc2.e3	3.48	0.21	1.27	2.98	10.63	0.07	1	5.23	0.4	4.5	3.62	8.85	1.61	1.04
md.oclstr.fc.nc2.e4	4.44	0.31	1.55	3.41	10.84	0.1	1	4.99	0.41	4.54	4.03	9.02	0.97	1.05
md.oclstr.fc.nc2.e5	4.44	0.31	1.55	3.41	10.84	0.1	1	4.99	0.41	4.54	4.03	9.02	0.97	1.05
md.oclstr.fc.nc3.e1	0.19	0	0.08	0.23	0.74	0	1	506.46	5074.2	503.7	500.92	1007.38	5.55	-4.01
md.oclstr.fc.nc3.e2	3.63	0.2	1.24	2.61	8.1	0.24	1	200.42	770.2	196.24	191.96	392.39	8.46	-0.92
md.oclstr.fc.nc3.e3	6.81	0.61	2.16	3.8	13.86	0.62	1.01	20.73	7.43	19.27	17.7	38.43	3.03	0.82
md.oclstr.fc.nc3.e4	9.32	1.12	2.93	4.98	17.42	0.09	1.01	0.86	0.01	0.64	0.26	1.13	0.6	1
md.oclstr.fc.nc3.e5	9.32	1.12	2.93	4.98	17.42	0.09	1.01	0.86	0.01	0.64	0.26	1.13	0.6	1
md.oclstr.km.nc1.e1	2.18	0.07	0.75	1.63	6.35	0.15	1	20.7	6.44	17.95	14.69	35.39	6.01	1.21
md.oclstr.km.nc1.e2	2.24	0.08	0.78	1.67	6.35	0.22	1	19.22	5.98	17.29	15.12	34.34	4.1	1.19
md.oclstr.km.nc1.e3	7.97	0.8	2.48	4.07	13.6	0.73	1.01	16.1	2.63	11.47	2.04	18.14	14.06	0.98
md.oclstr.km.nc1.e4	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.km.nc1.e5	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.km.nc2.e1	1.4	0.05	0.63	1.79	5.79	0.01	1	25.5	6.91	18.58	6.35	31.86	19.15	1.26
md.oclstr.km.nc2.e2	5.6	0.45	1.86	3.72	14.15	0.42	1	8.07	0.65	5.71	0.27	8.33	7.8	1.08
md.oclstr.km.nc2.e3	5.73	0.51	1.98	4.26	13.51	0.41	0.99	10.24	1.07	7.31	1.46	11.7	8.78	1.1
md.oclstr.km.nc2.e4	9.37	1.73	3.64	9.2	32.56	0.7	1.01	18.67	6.15	17.54	16.34	35.01	2.33	1.19
md.oclstr.km.nc2.e5	9.37	1.73	3.64	9.2	32.56	0.7	1.01	18.67	6.15	17.54	16.34	35.01	2.33	1.19
md.oclstr.km.nc3.e1	1.42	0.05	0.6	1.64	4.85	0.05	1	16.94	4.41	14.84	12.4	29.34	4.55	0.83
md.oclstr.km.nc3.e2	3.8	0.22	1.29	2.7	9.82	0.05	1	16.95	4.38	14.79	12.26	29.21	4.7	0.88
md.oclstr.km.nc3.e3	4.41	0.4	1.76	4.58	14.75	0.09	1	19.03	5.06	15.91	12	31.03	7.03	0.88
md.oclstr.km.nc3.e4	6.42	0.77	2.44	6	20.45	0.23	1	4.23	0.21	3.22	1.68	5.91	2.55	1.04
md.oclstr.km.nc3.e5	6.42	0.77	2.44	6	20.45	0.23	1	4.23	0.21	3.22	1.68	5.91	2.55	1.04
md.oclstr.km.nc4.e1	1.32	0.03	0.49	1.16	3.89	0	1	34.62	12.91	25.41	9.64	44.26	24.97	0.9

Table B: continued

oclstr=ortho-clustering, fc = fuzzy c-means clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)
nc = no. clusters, md = data prepared using median, with SAIL R&D's experience, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modeling	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.oclstr.km.nc4.e2	3.76	0.22	1.29	2.74	9.08	0.5	0.99	39.08	17.72	29.77	15.64	54.72	23.44	0.84
md.oclstr.km.nc4.e3	5.41	0.35	1.64	2.39	10.29	2.41	0.99	39.69	17.81	29.84	14.33	54.02	25.36	0.86
md.oclstr.km.nc4.e4	9.06	1.3	3.16	6.91	25.76	3.35	1	39.66	17.79	29.82	14.36	54.02	25.3	0.86
md.oclstr.km.nc4.e5	9.06	1.3	3.16	6.91	25.76	3.35	1	39.66	17.79	29.82	14.36	54.02	25.3	0.86
md.oclstr.km.nc5.e1	0.71	0.01	0.27	0.66	1.74	0	1	27.82	9.03	21.25	11.35	39.17	16.47	1.28
md.oclstr.km.nc5.e2	3.34	0.15	1.06	1.85	7.18	1.11	1	27.82	9.03	21.25	11.35	39.17	16.47	1.28
md.oclstr.km.nc5.e3	5.19	0.55	2.07	5.34	20.87	1.11	1	27.81	9.02	21.24	11.35	39.16	16.47	1.28
md.oclstr.km.nc5.e4	6.89	0.9	2.63	6.51	20.87	0.79	1.01	27.81	9.02	21.24	11.35	39.16	16.47	1.28
md.oclstr.km.nc5.e5	8.69	1.44	3.33	8.27	25.77	0.79	1.01	27.79	9	21.22	11.32	39.1	16.47	1.28
md.oclstr.kh.nc1.e1	2.18	0.07	0.75	1.63	6.35	0.15	1	20.7	6.44	17.95	14.69	35.39	6.01	1.21
md.oclstr.kh.nc1.e2	2.24	0.08	0.78	1.67	6.35	0.22	1	19.22	5.98	17.29	15.12	34.34	4.1	1.19
md.oclstr.kh.nc1.e3	7.97	0.8	2.48	4.07	13.6	0.73	1.01	16.1	2.63	11.47	2.04	18.14	14.06	0.98
md.oclstr.kh.nc1.e4	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.kh.nc1.e5	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.at.nc5.e1	2.18	0.07	0.75	1.63	6.35	0.15	1	20.7	6.44	17.95	14.69	35.39	6.01	1.21
md.oclstr.at.nc5.e2	2.24	0.08	0.78	1.67	6.35	0.22	1	19.22	5.98	17.29	15.12	34.34	4.1	1.19
md.oclstr.at.nc5.e3	7.97	0.8	2.48	4.07	13.6	0.73	1.01	16.1	2.63	11.47	2.04	18.14	14.06	0.98
md.oclstr.at.nc5.e4	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.at.nc5.e5	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.fa.nc5.e1	2.18	0.07	0.75	1.63	6.35	0.15	1	20.7	6.44	17.95	14.69	35.39	6.01	1.21
md.oclstr.fa.nc5.e2	2.24	0.08	0.78	1.67	6.35	0.22	1	19.22	5.98	17.29	15.12	34.34	4.1	1.19
md.oclstr.fa.nc5.e3	7.97	0.8	2.48	4.07	13.6	0.73	1.01	16.1	2.63	11.47	2.04	18.14	14.06	0.98
md.oclstr.fa.nc5.e4	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06
md.oclstr.fa.nc5.e5	11.35	2.14	4.06	9.25	32.71	1.6	1.02	6.38	0.41	4.53	0.59	6.97	5.79	1.06

Table B: continued

oclstr=ortho-clustering, kh=SOM clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)
nc = no. clusters, md = data prepared using median, with SAIL R&D's experience , mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modelling	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
md.autregrma.v1.pol	5.34	0.49	2.02	4.53	15.66	0.14	0.98	17.98	3.33	12.9	3.09	21.08	14.89	0.97
md.autregrma.v1.sin	5.49	0.58	2.2	5.28	16.02	0.16	0.98	23.7	5.84	17.09	4.78	28.47	18.92	1.05
md.autregrma.v1.tnh	6.29	0.69	2.4	5.44	17	0.7	0.98	27.66	9.62	21.93	14.05	41.71	13.61	1.14
md.autregrma.v1.exp	2.2	0.06	0.71	1.12	3.75	0.36	0.98	5.47	0.3	3.87	0.28	5.74	5.19	1
md.autregrma.v2.pol	6.26	0.63	2.28	4.84	16.58	0.16	1.02	21.95	4.83	15.55	1.26	23.21	20.69	1.01
md.autregrma.v2.sin	6.9	0.68	2.38	4.52	16.75	1.41	1.02	26.53	8.42	20.52	11.76	38.29	14.77	1.12
md.autregrma.v2.tnh	7.36	0.78	2.55	4.88	17.28	0.1	1.02	29.03	12.13	24.62	19.23	48.26	9.8	1.19
md.autregrma.v2.exp	4.2	0.27	1.5	3.03	11.15	0.3	1.03	20.24	4.26	14.59	3.97	24.21	16.27	1.2
md.autregrma.v3.pol	2.37	0.07	0.77	1.22	4.57	0.43	0.98	10.8	1.17	7.65	0.76	11.55	10.04	0.99
md.autregrma.v3.sin	2.82	0.13	1.05	2.32	8.42	0.13	0.98	28.91	9.55	21.85	10.91	39.82	18	1.11
md.autregrma.v3.tnh	2.76	0.14	1.07	2.46	9.23	0.31	0.98	39.48	26.1	36.12	32.42	71.9	7.06	1.32
md.autregrma.v3.exp	2.36	0.06	0.68	0.12	2.6	2.15	0.98	5.09	0.27	3.67	1.01	6.11	4.08	1.01
md.autregrma.v4.pol	2.37	0.07	0.77	1.24	4.73	0.16	0.98	10.46	1.1	7.42	0.85	11.31	9.61	0.99
md.autregrma.v4.sin	2.94	0.13	1.05	2.14	8.67	0.84	0.98	29.01	9.65	21.97	11.1	40.11	17.91	1.11
md.autregrma.v4.tnh	2.73	0.13	1.05	2.38	9.51	0.32	0.98	39.84	26.85	36.64	33.14	72.97	6.7	1.33
md.autregrma.v4.exp	2.35	0.06	0.7	0.55	3.47	1.26	0.98	4.62	0.22	3.34	0.96	5.58	3.65	1.01
md.autregrma.v5.pol	1.04	0.02	0.36	0.7	2.25	0.07	1	11.06	1.25	7.91	1.65	12.71	9.41	1.02
md.autregrma.v5.sin	2.31	0.08	0.82	1.66	6.19	0	1	29.61	10.62	23.04	13.6	43.22	16.01	1.14
md.autregrma.v5.tnh	2.24	0.09	0.84	1.88	7.03	0.19	1	40.44	29.05	38.11	35.64	76.08	4.8	1.36
md.autregrma.v5.exp	0.1	0	0.03	0.07	0.24	0.02	1	5.22	0.39	4.43	3.47	8.68	1.75	1.03

Table B: continued

autregrma = ARMA, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic, exponential modeling functions
nc = no. clusters, md = data prepared using median, with SAIL R&D's experience, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
rd.simplregr.v1.pol	6.65	0.73	2.36	5.34	18.7	0.45	1.02	16.79	3.33	12.91	7.18	23.97	9.61	1.1
rd.simplregr.v1.sin	8.55	1.13	2.95	6.33	19.31	1.44	1.03	16.68	2.99	12.23	4.54	21.22	12.15	1.1
rd.simplregr.v1.tnh	9.65	1.36	3.24	6.59	21.03	2.13	1.03	17.13	4.67	15.28	13.17	30.3	3.96	1.1
rd.simplregr.v1.exp	1.67	0.06	0.68	1.78	5.73	0.04	1.02	26.59	7.26	19.05	4.39	30.98	22.19	1.2
rd.simplregr.v2.pol	6.61	0.8	2.48	6	20.03	0.02	1.04	18.34	3.9	13.97	7.33	25.68	11.01	1.1
rd.simplregr.v2.sin	8.26	1.22	3.07	7.35	20.71	0.29	1.04	18	3.44	13.11	4.43	22.43	13.58	1.1
rd.simplregr.v2.tnh	9.4	1.47	3.36	7.65	22.46	1.06	1.04	18.39	5.1	15.97	13.11	31.5	5.28	1.1
rd.simplregr.v2.exp	3.01	0.12	0.98	1.82	7.11	1.11	1.03	28.34	8.21	20.26	4.23	32.57	24.11	1.2
rd.simplregr.v3.pol	2.54	0.1	0.86	1.78	6.93	0.32	0.98	26.77	8.92	21.12	13.24	40.01	13.53	1.1
rd.simplregr.v3.sin	4.68	0.3	1.53	2.92	11.96	0.67	0.98	41.87	17.71	29.76	4.22	46.09	37.66	1.0
rd.simplregr.v3.tnh	5.6	0.43	1.81	3.38	11.77	1.08	0.98	48.68	23.7	34.42	0.08	48.76	48.6	1
rd.simplregr.v3.exp	2.36	0.06	0.66	0.14	2.61	2	0.98	29.1	14.44	26.87	24.44	53.54	4.66	1.29
rd.simplregr.v4.pol	2.58	0.1	0.88	1.86	7.56	0.33	0.98	27.65	9.44	21.72	13.4	41.04	14.25	1.13
rd.simplregr.v4.sin	4.66	0.31	1.55	3.06	12.72	0.79	0.98	43.12	18.76	30.63	4.15	47.27	38.96	1.04
rd.simplregr.v4.tnh	5.6	0.43	1.82	3.44	12.52	1.22	0.98	50.09	25.09	35.42	0.08	50.17	50.01	1
rd.simplregr.v4.exp	2.44	0.06	0.68	0.38	3.03	1.61	0.98	29.65	14.94	27.33	24.8	54.45	4.84	1.3
rd.simplregr.v5.pol	1.6	0.04	0.58	1.35	4.67	0.07	1	27.42	10.07	22.44	15.99	43.4	11.43	1.16
rd.simplregr.v5.sin	3.83	0.27	1.45	3.56	10.86	0.18	1	42.89	18.85	30.7	6.74	49.63	36.15	1.07
rd.simplregr.v5.tnh	4.77	0.41	1.78	4.28	14.18	0.26	1	49.86	24.92	35.3	2.51	52.37	47.35	1.03
rd.simplregr.v5.exp	0.11	0	0.04	0.1	0.38	0.03	1	32.23	16.66	28.86	25.03	57.27	7.2	1.32
rd.cr.fc.v1.pol.nc2	2.55	0.1	0.86	1.75	5.92	0.1	1.02	29.34	9.33	21.6	8.51	37.85	20.83	0.91
rd.cr.fc.v1.pol.nc3	1.67	0.04	0.57	1.23	4.36	0.06	1.02	14.28	3.83	13.84	13.38	27.66	0.91	1.14
rd.cr.fc.v1.pol.nc4	1.63	0.03	0.51	0.85	2.85	0.19	1.02	5.04	0.42	4.6	4.13	9.16	0.91	1.05
rd.cr.fc.v1.pol.nc5	1.59	0.03	0.48	0.67	2.85	0.59	1.02	14.73	2.48	11.14	5.57	20.3	9.16	0.94
rd.cr.fc.v1.sin.nc2	2.47	0.08	0.79	1.42	4.9	0.09	1.02	18.53	3.7	13.61	5.2	23.73	13.33	1.05
rd.cr.fc.v1.sin.nc3	1.72	0.04	0.58	1.21	3.69	0.08	1.02	17.79	3.52	13.26	5.94	23.73	11.85	1.18
rd.cr.fc.v1.sin.nc4	1.67	0.04	0.55	1.05	3.07	0	1.02	5.76	0.46	4.81	3.61	9.37	2.14	1.06
rd.cr.fc.v1.sin.nc5	1.61	0.03	0.49	0.76	2.92	0.08	1.02	7.24	0.57	5.33	2.13	9.37	5.11	1.02
rd.cr.fc.v1.tnh.nc2	2.43	0.08	0.76	1.3	4.32	0.21	1.02	14.41	2.94	12.13	9.32	23.73	5.09	1.09
rd.cr.fc.v1.tnh.nc3	1.79	0.05	0.6	1.22	3.63	0.19	1.02	17.87	3.54	13.3	5.86	23.73	12.01	1.18

Table C: performance statistics of all models on problem of estimation of life of converter lining (mean R&D)

* simplregr = simple rigression, cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean, with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slop
rd.cr.fc.v1.tnh.nc4	1.74	0.04	0.57	1.1	3.2	0.11	1.02	6.34	0.48	4.9	2.82	9.15	3.52	1
rd.cr.fc.v1.tnh.nc5	1.64	0.03	0.51	0.86	3.24	0.04	1.02	5.58	0.44	4.69	3.58	9.15	2	1
rd.cr.fc.v1.exp.nc2	1.59	0.03	0.46	0.43	2.49	0.9	1.02	23.4	5.71	16.9	4.88	28.29	18.52	1
rd.cr.fc.v1.exp.nc3	1.58	0.03	0.45	0.39	2.35	1.01	1.02	14.81	4.01	14.16	13.48	28.29	1.33	1
rd.cr.fc.v1.exp.nc4	1.58	0.03	0.45	0.35	2.38	1.06	1.02	10.6	2.2	10.48	10.35	20.95	0.25	1
rd.cr.fc.v1.exp.nc5	1.57	0.03	0.45	0.35	2.38	1.06	1.02	6.51	0.81	6.38	6.26	12.76	0.25	1
rd.cr.fc.v2.pol.nc2	3.46	0.16	1.12	2.08	7.22	0.26	1.03	30.99	10.25	22.64	8.01	39	22.98	0.
rd.cr.fc.v2.pol.nc3	3.03	0.11	0.9	1.2	5.67	1.44	1.03	16.17	4.45	14.91	13.53	29.7	2.64	1.
rd.cr.fc.v2.pol.nc4	2.99	0.1	0.86	0.83	4.17	1.6	1.03	6.48	0.57	5.33	3.84	10.32	2.64	1.
rd.cr.fc.v2.pol.nc5	2.95	0.09	0.84	0.65	4.17	1.99	1.03	15.43	2.64	11.49	5.11	20.54	10.32	0.
rd.cr.fc.v2.sin.nc2	3.4	0.15	1.07	1.82	6.23	0.11	1.03	19.49	4.25	14.58	6.72	26.21	12.76	1.
rd.cr.fc.v2.sin.nc3	3.06	0.11	0.91	1.21	5.02	1.29	1.03	19.91	4.36	14.77	6.3	26.21	13.6	1.
rd.cr.fc.v2.sin.nc4	3.03	0.1	0.89	1.02	4.39	1.4	1.03	7.17	0.63	5.61	3.39	10.56	3.77	1.0
rd.cr.fc.v2.sin.nc5	2.98	0.09	0.85	0.74	4.24	1.48	1.03	7.26	0.64	5.64	3.3	10.56	3.97	1.0
rd.cr.fc.v2.tnh.nc2	3.36	0.14	1.05	1.75	5.64	0.06	1.03	15.12	3.52	13.27	11.11	26.23	4.02	1.1
rd.cr.fc.v2.tnh.nc3	3.08	0.11	0.92	1.28	4.96	1.14	1.03	19.98	4.38	14.8	6.25	26.23	13.73	1.
rd.cr.fc.v2.tnh.nc4	3.05	0.11	0.9	1.13	4.52	1.23	1.03	7.73	0.67	5.77	2.6	10.33	5.13	1.0
rd.cr.fc.v2.tnh.nc5	2.99	0.1	0.86	0.85	4.55	1.37	1.03	5.54	0.54	5.18	4.79	10.33	0.75	1.0
rd.cr.fc.v2.exp.nc2	2.96	0.09	0.83	0.44	3.87	2.24	1.03	23.15	6	17.32	8	31.15	15.15	1.0
rd.cr.fc.v2.exp.nc3	2.95	0.09	0.83	0.39	3.73	2.37	1.03	16.88	4.89	15.63	14.26	31.15	2.62	1.1
rd.cr.fc.v2.exp.nc4	2.94	0.09	0.82	0.36	3.77	2.42	1.03	12.84	2.81	11.85	10.77	23.61	2.07	1.13
rd.cr.fc.v2.exp.nc5	2.94	0.09	0.82	0.36	3.77	2.42	1.03	7.79	0.93	6.83	5.72	13.5	2.07	1.08
rd.cr.fc.v3.pol.nc2	2.37	0.06	0.66	0.1	2.48	2.17	0.98	8.1	0.67	5.78	1.05	9.16	7.05	0.99
rd.cr.fc.v3.pol.nc3	2.36	0.06	0.66	0.1	2.54	2.2	0.98	10.15	1.26	7.94	4.79	14.94	5.36	1.05
rd.cr.fc.v3.pol.nc4	2.37	0.06	0.66	0.09	2.54	2.22	0.98	6.72	0.47	4.85	1.36	8.08	5.36	1.01
rd.cr.fc.v3.pol.nc5	2.37	0.06	0.66	0.07	2.49	2.25	0.98	6.61	0.46	4.79	1.47	8.08	5.13	1.01
rd.cr.fc.v3.sin.nc2	2.36	0.06	0.66	0.12	2.49	2.11	0.98	6.36	0.41	4.52	0.67	7.02	5.69	1.01
rd.cr.fc.v3.sin.nc3	2.36	0.06	0.66	0.11	2.59	2.18	0.98	5.27	0.31	3.93	1.75	7.02	3.52	1.05
rd.cr.fc.v3.sin.nc4	2.37	0.06	0.66	0.11	2.59	2.18	0.98	6.24	0.44	4.7	2.3	8.53	3.94	1.02
rd.cr.fc.v3.sin.nc5	2.37	0.06	0.66	0.08	2.54	2.23	0.98	6.61	0.47	4.87	1.92	8.53	4.69	1.02
rd.cr.fc.v3.tnh.nc2	2.36	0.06	0.66	0.14	2.52	2.07	0.98	5.78	0.34	4.15	0.97	6.75	4.81	1.01
rd.cr.fc.v3.tnh.nc3	2.36	0.06	0.66	0.13	2.61	2.15	0.98	4.84	0.27	3.68	1.91	6.75	2.93	1.05

Table C: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method	training statistics							prediction statistics					
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error
rd.cr.fc.v3.tnh.nc4	2.36	0.06	0.66	0.13	2.62	2.15	0.98	5.91	0.43	4.62	2.77	8.68	3.15
rd.cr.fc.v3.tnh.nc5	2.37	0.06	0.66	0.09	2.57	2.21	0.98	6.06	0.44	4.67	2.62	8.68	3.44
rd.cr.fc.v3.exp.nc2	2.37	0.06	0.66	0.03	2.4	2.29	0.98	16.72	2.8	11.84	0.77	17.49	15.95
rd.cr.fc.v3.exp.nc3	2.37	0.06	0.66	0.04	2.42	2.29	0.98	9.58	1.32	8.14	6.37	15.95	3.21
rd.cr.fc.v3.exp.nc4	2.37	0.06	0.66	0.02	2.41	2.33	0.98	7.44	0.57	5.36	1.39	8.84	6.05
rd.cr.fc.v3.exp.nc5	2.37	0.06	0.66	0.03	2.41	2.31	0.98	8.36	0.75	6.13	2.31	10.67	6.05
rd.cr.fc.v4.pol.nc2	2.43	0.06	0.68	0.33	2.89	1.65	0.98	8.39	0.72	6	1.26	9.65	7.13
rd.cr.fc.v4.pol.nc3	2.43	0.06	0.68	0.33	3.09	1.75	0.98	10.45	1.32	8.14	4.81	15.26	5.64
rd.cr.fc.v4.pol.nc4	2.43	0.06	0.68	0.32	3.09	1.75	0.98	6.88	0.49	4.94	1.24	8.12	5.64
rd.cr.fc.v4.pol.nc5	2.43	0.06	0.68	0.34	3.33	1.87	0.98	6.83	0.48	4.92	1.29	8.12	5.54
rd.cr.fc.v4.sin.nc2	2.43	0.06	0.68	0.31	2.87	1.7	0.98	6.6	0.44	4.68	0.5	7.1	6.1
rd.cr.fc.v4.sin.nc3	2.43	0.06	0.68	0.31	3.06	1.77	0.98	5.27	0.31	3.95	1.83	7.1	3.44
rd.cr.fc.v4.sin.nc4	2.43	0.06	0.68	0.31	3.06	1.77	0.98	6.39	0.46	4.78	2.2	8.58	4.19
rd.cr.fc.v4.sin.nc5	2.43	0.06	0.68	0.33	3.3	1.89	0.98	6.77	0.49	4.96	1.82	8.58	4.95
rd.cr.fc.v4.tnh.nc2	2.43	0.06	0.68	0.29	2.86	1.73	0.98	6.02	0.37	4.29	0.81	6.83	5.21
rd.cr.fc.v4.tnh.nc3	2.42	0.06	0.68	0.3	3.03	1.8	0.98	4.83	0.27	3.7	2	6.83	2.83
rd.cr.fc.v4.tnh.nc4	2.43	0.06	0.68	0.29	3.03	1.8	0.98	6.06	0.44	4.68	2.68	8.74	3.37
rd.cr.fc.v4.tnh.nc5	2.43	0.06	0.68	0.32	3.27	1.91	0.98	6.21	0.45	4.74	2.53	8.74	3.68
rd.cr.fc.v4.exp.nc2	2.43	0.06	0.68	0.36	2.94	1.6	0.98	17.25	2.98	12.22	0.95	18.2	18.3
rd.cr.fc.v4.exp.nc3	2.43	0.06	0.68	0.37	3.14	1.7	0.98	9.87	1.39	8.33	6.43	16.3	3.44
rd.cr.fc.v4.exp.nc4	2.42	0.06	0.68	0.38	3.38	1.83	0.98	7.72	0.61	5.53	1.24	8.96	6.48
rd.cr.fc.v4.exp.nc5	2.42	0.06	0.68	0.37	3.38	1.83	0.98	8.63	0.79	6.29	2.14	10.77	6.48
rd.cr.fc.v5.pol.nc2	0.09	0	0.03	0.05	0.2	0.01	1	8.3	0.71	5.94	1.35	9.64	6.95
rd.cr.fc.v5.pol.nc3	0.09	0	0.03	0.05	0.18	0.02	1	10.4	1.62	8.99	7.33	17.73	3.06
rd.cr.fc.v5.pol.nc4	0.08	0	0.02	0.05	0.18	0.02	1	6.88	0.62	5.57	3.82	10.7	3.06
rd.cr.fc.v5.pol.nc5	0.06	0	0.02	0.04	0.13	0	1	6.77	0.61	5.54	3.93	10.7	2.83
rd.cr.fc.v5.sin.nc2	0.1	0	0.04	0.08	0.26	0	1	6.51	0.52	5.1	3.11	9.62	3.4
rd.cr.fc.v5.sin.nc3	0.1	0	0.03	0.06	0.22	0.01	1	7.82	0.64	5.68	1.8	9.62	6.03
rd.cr.fc.v5.sin.nc4	0.1	0	0.03	0.06	0.22	0.03	1	6.39	0.64	5.64	4.78	11.16	1.61
rd.cr.fc.v5.sin.nc5	0.07	0	0.02	0.05	0.18	0	1	6.77	0.65	5.71	4.39	11.16	2.38
rd.cr.fc.v5.tnh.nc2	0.12	0	0.04	0.09	0.3	0	1	5.92	0.47	4.84	3.42	9.34	2.51
rd.cr.fc.v5.tnh.nc3	0.11	0	0.04	0.07	0.25	0.02	1	7.38	0.58	5.4	1.96	9.34	5.42
rd.cr.fc.v5.tnh.nc4	0.11	0	0.04	0.06	0.25	0.04	1	6.06	0.64	5.67	5.26	11.32	0.8
rd.cr.fc.v5.tnh.nc5	0.08	0	0.03	0.06	0.2	0	1	6.21	0.65	5.68	5.11	11.32	1.1

Table C: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
rd.cr.fc.v5.exp.nc2	0.03	0	0.01	0.02	0.08	0	1	17.13	2.96	12.17	1.64	18.77	15.49	1.0
rd.cr.fc.v5.exp.nc3	0.03	0	0.01	0.02	0.08	0	1	9.82	1.76	9.39	8.95	18.77	0.87	1.0
rd.cr.fc.v5.exp.nc4	0.02	0	0.01	0.01	0.04	0	1	7.63	0.73	6.04	3.85	11.48	3.77	1.0
rd.cr.fc.v5.exp.nc5	0.02	0	0.01	0.02	0.06	0	1	8.56	0.96	6.94	4.79	13.35	3.77	1.0
rd.cr.km.v1.pol.nc2	2.25	0.09	0.81	1.87	5.65	0.2	1.02	12.08	1.5	8.65	1.91	13.99	10.18	1.1
rd.cr.km.v1.pol.nc3	1.68	0.04	0.55	1.09	3.8	0.1	1.02	16.49	2.91	12.06	4.34	20.83	12.15	1.1
rd.cr.km.v1.pol.nc4	1.66	0.04	0.54	1	3.8	0.1	1.02	20.57	4.23	14.54	0.26	20.83	20.3	1
rd.cr.km.v1.pol.nc5	1.61	0.03	0.48	0.63	2.7	0.59	1.02	14.73	2.48	11.14	5.57	20.3	9.16	0.9
rd.cr.km.v1.sin.nc2	2.21	0.08	0.77	1.65	5.01	0.18	1.02	12.65	1.67	9.15	2.71	15.36	9.94	1.1
rd.cr.km.v1.sin.nc3	1.72	0.04	0.58	1.21	3.69	0.08	1.02	17.79	3.52	13.26	5.94	23.73	11.85	1.1
rd.cr.km.v1.sin.nc4	1.69	0.04	0.57	1.17	3.69	0.08	1.02	14.42	2.95	12.14	9.31	23.73	5.11	1.0
rd.cr.km.v1.sin.nc5	1.65	0.04	0.52	0.89	2.92	0.08	1.02	7.24	0.57	5.33	2.13	9.37	5.11	1.0
rd.cr.km.v1.tnh.nc2	2.19	0.07	0.74	1.54	4.59	0.15	1.02	11.92	1.51	8.69	2.98	14.89	8.94	1.1
rd.cr.km.v1.tnh.nc3	1.79	0.05	0.6	1.22	3.63	0.19	1.02	17.87	3.54	13.3	5.86	23.73	12.01	1.1
rd.cr.km.v1.tnh.nc4	1.83	0.04	0.59	1.07	4.18	0.19	1.02	14.92	3.77	13.74	12.45	27.36	2.47	1.12
rd.cr.km.v1.tnh.nc5	1.71	0.04	0.54	0.96	3.14	0.04	1.02	5.58	0.44	4.69	3.58	9.15	2	1.04
rd.cr.km.v1.exp.nc2	1.59	0.03	0.46	0.5	2.35	0.77	1.02	37.84	17.84	29.87	18.78	56.62	19.06	1.38
rd.cr.km.v1.exp.nc3	1.57	0.03	0.45	0.33	2.35	1.01	1.02	19.28	3.96	14.07	4.89	24.18	14.39	1.19
rd.cr.km.v1.exp.nc4	1.58	0.03	0.45	0.35	2.35	1.01	1.02	10.6	2.2	10.48	10.35	20.95	0.25	1.11
rd.cr.km.v1.exp.nc5	1.57	0.03	0.45	0.32	2.35	1.01	1.02	6.51	0.81	6.38	6.26	12.76	0.25	1.07
rd.cr.km.v2.pol.nc2	3.28	0.15	1.08	2.11	6.99	0.72	1.03	12.74	1.67	9.14	2.17	14.9	10.57	1.13
rd.cr.km.v2.pol.nc3	3.03	0.1	0.89	1.09	5.13	1.3	1.03	18.49	3.62	13.45	4.5	22.98	13.99	1.18
rd.cr.km.v2.pol.nc4	3.01	0.1	0.88	1.01	5.13	1.3	1.03	21.76	4.75	15.41	1.22	22.98	20.54	1.01
rd.cr.km.v2.pol.nc5	2.97	0.09	0.84	0.61	4.03	1.98	1.03	15.43	2.64	11.49	5.11	20.54	10.32	0.95
rd.cr.km.v2.sin.nc2	3.23	0.14	1.05	1.96	6.34	0.39	1.03	13.65	1.95	9.87	2.92	16.56	10.73	1.14
rd.cr.km.v2.sin.nc3	3.06	0.11	0.91	1.21	5.02	1.29	1.03	19.91	4.36	14.77	6.3	26.21	13.6	1.2
rd.cr.km.v2.sin.nc4	3.05	0.11	0.9	1.14	5.02	1.48	1.03	15.09	3.51	13.25	11.12	26.21	3.97	1.11
rd.cr.km.v2.sin.nc5	3.01	0.1	0.87	0.87	4.24	1.48	1.03	7.26	0.64	5.64	3.3	10.56	3.97	1.03
rd.cr.km.v2.tnh.nc2	3.21	0.14	1.03	1.88	5.97	0.25	1.03	13.01	1.79	9.46	3.12	16.13	9.88	1.13
rd.cr.km.v2.tnh.nc3	3.08	0.11	0.92	1.28	4.96	1.14	1.03	19.98	4.38	14.8	6.25	26.23	13.73	1.2
rd.cr.km.v2.tnh.nc4	3.06	0.11	0.92	1.23	5.47	0.78	1.03	16.45	4.83	15.55	14.59	31.04	1.86	1.15
rd.cr.km.v2.tnh.nc5	3.03	0.1	0.89	0.99	4.46	1.23	1.03	5.54	0.54	5.18	4.79	10.33	0.75	1.05
rd.cr.km.v2.exp.nc2	2.96	0.09	0.83	0.5	3.73	2.17	1.03	39.92	19.43	31.17	18.7	58.62	21.23	1.4
rd.cr.km.v2.exp.nc3	2.94	0.09	0.82	0.33	3.73	2.37	1.03	21.41	4.96	15.75	6.13	27.54	15.28	1.21

Table c: continued

cr = cluster wise regression, fc = fuzzy c-means clustering,km= k-mean clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
rd.cr.km.v2.exp.nc4	2.95	0.09	0.82	0.36	3.73	2.37	1.03	12.84	2.81	11.85	10.77	23.61	2.07	1.13
rd.cr.km.v2.exp.nc5	2.94	0.09	0.82	0.33	3.73	2.37	1.03	7.79	0.93	6.83	5.72	13.5	2.07	1.08
rd.cr.km.v3.pol.nc2	2.36	0.06	0.66	0.08	2.55	2.27	0.98	6.1	0.6	5.49	4.8	10.9	1.29	1.06
rd.cr.km.v3.pol.nc3	2.37	0.06	0.66	0.08	2.54	2.22	0.98	5.77	0.35	4.18	1.28	7.05	4.5	1.06
rd.cr.km.v3.pol.nc4	2.37	0.06	0.66	0.07	2.49	2.25	0.98	6.09	0.38	4.36	0.96	7.05	5.13	1.01
rd.cr.km.v3.pol.nc5	2.37	0.06	0.66	0.06	2.49	2.25	0.98	6.61	0.46	4.79	1.47	8.08	5.13	1.01
rd.cr.km.v3.sin.nc2	2.36	0.06	0.66	0.14	2.63	2.15	0.98	6.56	0.84	6.46	6.37	12.92	0.19	1.07
rd.cr.km.v3.sin.nc3	2.36	0.06	0.66	0.11	2.59	2.18	0.98	5.27	0.31	3.93	1.75	7.02	3.52	1.05
rd.cr.km.v3.sin.nc4	2.37	0.06	0.66	0.09	2.54	2.23	0.98	5.86	0.36	4.22	1.17	7.02	4.69	1.01
rd.cr.km.v3.sin.nc5	2.37	0.06	0.66	0.08	2.54	2.23	0.98	6.61	0.47	4.87	1.92	8.53	4.69	1.02
rd.cr.km.v3.tnh.nc2	2.35	0.06	0.65	0.19	2.72	2.04	0.98	7.45	0.98	7.01	6.55	14	0.91	1.07
rd.cr.km.v3.tnh.nc3	2.36	0.06	0.66	0.13	2.61	2.15	0.98	4.84	0.27	3.68	1.91	6.75	2.93	1.05
rd.cr.km.v3.tnh.nc4	2.37	0.06	0.66	0.1	2.54	2.23	0.98	4.09	0.2	3.16	1.81	5.9	2.28	1.02
rd.cr.km.v3.tnh.nc5	2.37	0.06	0.66	0.1	2.57	2.21	0.98	6.06	0.44	4.67	2.62	8.68	3.44	1.03
rd.cr.km.v3.exp.nc2	2.36	0.06	0.66	0.08	2.46	2.16	0.98	35.48	18.18	30.15	23.65	59.13	11.83	1.35
rd.cr.km.v3.exp.nc3	2.37	0.06	0.66	0.03	2.43	2.31	0.98	10.37	1.12	7.47	2	12.37	8.37	1.1
rd.cr.km.v3.exp.nc4	2.37	0.06	0.66	0.02	2.41	2.33	0.98	7.44	0.57	5.36	1.39	8.84	6.05	1.01
rd.cr.km.v3.exp.nc5	2.37	0.06	0.66	0.02	2.41	2.33	0.98	8.36	0.75	6.13	2.31	10.67	6.05	1.02
rd.cr.km.v4.pol.nc2	2.44	0.06	0.68	0.35	2.94	1.68	0.98	6.06	0.63	5.62	5.15	11.21	0.91	1.06
rd.cr.km.v4.pol.nc3	2.43	0.06	0.68	0.33	3.09	1.75	0.98	5.79	0.35	4.2	1.34	7.13	4.44	1.06
rd.cr.km.v4.pol.nc4	2.43	0.06	0.68	0.34	3.09	1.75	0.98	6.34	0.41	4.52	0.79	7.13	5.54	1.01
rd.cr.km.v4.pol.nc5	2.43	0.06	0.68	0.33	3.09	1.75	0.98	6.83	0.48	4.92	1.29	8.12	5.54	1.01
rd.cr.km.v4.sin.nc2	2.43	0.06	0.68	0.32	2.89	1.72	0.98	6.75	0.88	6.64	6.53	13.28	0.22	1.07
rd.cr.km.v4.sin.nc3	2.43	0.06	0.68	0.31	3.06	1.77	0.98	5.27	0.31	3.95	1.83	7.1	3.44	1.05
rd.cr.km.v4.sin.nc4	2.43	0.06	0.68	0.32	3.06	1.77	0.98	6.03	0.37	4.33	1.08	7.1	4.95	1.01
rd.cr.km.v4.sin.nc5	2.43	0.06	0.68	0.32	3.06	1.77	0.98	6.77	0.49	4.96	1.82	8.58	4.95	1.02
rd.cr.km.v4.tnh.nc2	2.43	0.06	0.68	0.31	2.85	1.74	0.98	7.87	1.04	7.22	6.52	14.38	1.35	1.07
rd.cr.km.v4.tnh.nc3	2.42	0.06	0.68	0.3	3.03	1.8	0.98	4.83	0.27	3.7	2	6.83	2.83	1.05
rd.cr.km.v4.tnh.nc4	2.44	0.06	0.68	0.34	3.03	1.8	0.98	4.42	0.22	3.34	1.68	6.1	2.74	1.02
rd.cr.km.v4.tnh.nc5	2.43	0.06	0.68	0.3	3.03	1.8	0.98	6.21	0.45	4.74	2.53	8.74	3.68	1.03
rd.cr.km.v4.exp.nc2	2.44	0.06	0.68	0.38	3.14	1.7	0.98	36.2	18.86	30.71	24	60.19	12.2	1.36
rd.cr.km.v4.exp.nc3	2.43	0.06	0.68	0.36	3.14	1.7	0.98	10.29	1.11	7.45	2.29	12.58	8	1.1
rd.cr.km.v4.exp.nc4	2.43	0.06	0.68	0.37	3.14	1.7	0.98	7.72	0.61	5.53	1.24	8.96	6.48	1.01
rd.cr.km.v4.exp.nc5	2.43	0.06	0.68	0.36	3.14	1.7	0.98	8.63	0.79	6.29	2.14	10.77	6.48	1.02

Table C: continued

cr = cluster wise regression, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	Training statistics: mn error	ms error	rms error	error std	max error	min error	slope	Prediction statistics: mn error	ms error	rms error	error std	max error	min error	slope
rd.cr.km.v5.pol.nc2	0.07	0	0.02	0.04	0.18	0.01	1	8.67	0.99	7.05	4.92	13.59	3.75	1.09
rd.cr.km.v5.pol.nc3	0.03	0	0.03	0.05	0.18	0.01	1	[illegible]	0.71	5.97	1.31	9.64	7.03	1.06
rd.cr.km.v5.pol.nc4	0.08	0	0.02	0.04	0.13	0	1	6.24	0.51	5.03	3.41	9.64	2.83	1.03
rd.cr.km.v5.pol.nc5	0.05	0	0.02	0.04	0.13	0	1	6.77	0.61	5.54	3.93	10.7	2.83	1.04
rd.cr.km.v5.sin.nc2	0.12	0	0.04	0.07	0.27	0.01	1	9.14	1.26	7.94	6.52	15.66	2.62	1.09
rd.cr.km.v5.sin.nc3	0.1	0	0.03	0.06	0.22	0.01	1	7.82	0.64	5.68	1.8	9.62	6.03	1.08
rd.cr.km.v5.sin.nc4	0.08	0	0.03	0.05	0.18	0.01	1	6	0.49	4.95	3.62	9.62	2.38	1.04
rd.cr.km.v5.sin.nc5	0.07	0	0.02	0.05	0.18	0.01	1	6.77	0.65	5.71	4.39	11.16	2.38	1.04
rd.cr.km.v5.tnh.nc2	0.17	0	0.05	0.1	0.36	0.01	1	9.13	1.42	8.42	7.03	10.77	1.5	1.09
rd.cr.km.v5.tnh.nc3	0.11	0	[illegible]	[illegible]	[illegible]	[illegible]	1	7.38	0.58	5.4	1.96	9.34	5.42	1.07
rd.cr.km.v5.tnh.nc4	0.09	0	0.03	0.05	0.18	0.01	1	4.28	0.36	4.24	4.19	8.47	0.09	1.04
rd.cr.km.v5.tnh.nc5	0.08	0	0.03	0.05	0.2	0.01	1	6.21	0.65	5.68	5.11	11.32	1.1	1.05
rd.cr.km.v5.exp.nc2	0.07	0	0.02	0.05	0.21	0.01	1	38.76	20.89	32.32	24.22	62.09	14.54	1.39
rd.cr.km.v5.exp.nc3	0.02	0	0.01	0.02	0.06	0	1	13.05	1.74	9.34	2.05	15.1	11	1.13
rd.cr.km.v5.exp.nc4	0.02	0	0.01	0.01	0.04	0	1	7.63	0.73	6.04	3.85	11.48	3.77	1.04
rd.cr.km.v5.exp.nc5	0.02	0	0.01	0.01	0.04	0	1	8.56	0.96	6.94	4.79	13.35	3.77	1.05
rd.cr.kh.v1.pol.nc2	2.24	0.08	0.77	1.62	6.38	0.2	1.88	21.8	5.33	18.32	7.58	28.38	14.23	0.82
rd.cr.kh.v1.pol.nc3	3.33	0.07	0.75	1.56	6.48	0.8	1.05	10.34	3.15	15.49	0.90	33.5	8.38	0.83
rd.cr.kh.v1.pol.nc4	1.81	[illegible]	[illegible]	1.68	1.7	0.15	1.02	20.35	6.34	17.8	14.82	35.17	5.53	1.2
rd.cr.kh.v1.pol.nc5	1.57	0.03	0.48	0.76	3.16	0.49	1.02	7.99	1.09	7.37	6.69	14.69	1.3	1.08
rd.cr.kh.v1.sin.nc2	2.33	0.08	0.8	1.7	7.06	0.61	1.02	18.78	3.6	13.42	2.74	21.52	18.64	0.87
rd.cr.kh.v1.sin.nc3	2.14	0.09	0.09	2.02	8.31	0.13	1.03	3.45	0.15	3.73	1.73	5.18	1.73	1.03
rd.cr.kh.v1.sin.nc4	1.03	0.05	0.81	1.23	4.48	0.28	1.02	23.65	8.63	20.77	17.42	41.07	6.23	1.24
rd.cr.kh.v1.sin.nc5	1.58	0.03	0.49	0.8	3.28	0.38	1.02	8.01	1.25	7.89	7.78	15.78	0.23	1.08
rd.cr.kh.v1.tnh.nc2	2.95	0.16	1.12	2.78	11.26	0.33	1.02	1.46	0.04	1.45	1.43	2.89	0.04	1.01
rd.cr.kh.v1.tnh.nc3	2.16	0.09	0.83	2.05	8.49	0.15	1.02	3.13	0.11	2.37	1.2	4.32	1.93	1.01
rd.cr.kh.v1.tnh.nc4	1.83	0.02	0.61	1.5	4.43	0.3	1.05	24.82	8.4	21.88	18.58	42.9	8.34	1.25
rd.cr.kh.v1.tnh.nc5	1.81	0.04	0.55	1.12	4.37	0.19	1.02	10.39	2.14	10.35	10.3	20.69	0.09	1.1
rd.cr.kh.v1.exp.nc2	1.63	0.03	0.52	0.89	3.17	0.43	1.02	7.94	0.69	5.87	2.43	10.37	5.51	1.02
rd.cr.kh.v1.exp.nc3	1.59	0.03	0.46	0.48	2.53	0.55	1.02	8.69	1.33	8.14	7.56	16.24	1.13	1.09
rd.cr.kh.v1.exp.nc4	1.6	0.03	0.48	0.66	3.34	0.74	1.02	19.99	1.79	9.47	0.1	13.49	13.3	1.13
rd.cr.kh.v1.exp.nc5	1.58	0.03	0.48	0.51	2.53	0.81	1.02	8.01	1.17	7.00	0.57	10.18	2.03	1.08
rd.cr.kh.v2.pol.nc2	3.35	0.14	1.05	1.79	7.67	0.88	1.03	22.88	5.69	16.87	6.77	29.65	16.11	0.93
rd.cr.kh.v2.pol.nc3	3.25	0.14	1.04	1.86	7.73	0.5	1.03	16.93	3.29	12.82	6.47	23.4	10.46	0.94

Table C: continued

cr = cluster wise regression, km=k-means clustering, kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
rd.cr.kh.v2.pol.nc4	3.06	0.11	0.93	1.42	5.97	0.75	1.03	22.63	7.73	19.66	16.15	38.78	6.48	1.23
rd.cr.kh.v2.pol.nc5	2.94	0.09	0.84	0.75	4.51	1.86	1.03	9.17	1.32	8.13	6.93	16.1	2.24	1.09
rd.cr.kh.v2.sin.nc2	3.36	0.15	1.08	1.94	8.32	0.69	1.03	19.75	3.93	14.01	1.61	21.36	18.14	0.98
rd.cr.kh.v2.sin.nc3	3.28	0.15	1.09	2.14	9.58	0.49	1.03	3.57	0.2	3.18	2.75	6.31	0.82	1.03
rd.cr.kh.v2.sin.nc4	3.06	0.11	0.93	1.38	5.76	0.77	1.03	26.12	10.4	22.8	18.91	45.03	7.21	1.26
rd.cr.kh.v2.sin.nc5	2.94	0.09	0.84	0.79	4.63	1.74	1.03	9.16	1.51	8.68	8.16	17.33	1	1.09
rd.cr.kh.v2.tnh.nc2	3.81	0.23	1.34	2.98	12.54	0.09	1.03	2.41	0.08	2	1.48	3.89	0.93	1.02
rd.cr.kh.v2.tnh.nc3	3.3	0.16	1.1	2.17	9.77	0.62	1.03	3.18	0.15	2.74	2.21	5.4	0.97	1.02
rd.cr.kh.v2.tnh.nc4	3.05	0.11	0.93	1.37	5.71	0.77	1.03	27.15	11.3	23.77	19.81	46.96	7.34	1.27
rd.cr.kh.v2.tnh.nc5	3	0.1	0.89	1.1	5.66	1.6	1.03	11.74	2.62	11.43	11.12	22.86	0.63	1.12
rd.cr.kh.v2.exp.nc2	3.01	0.1	0.87	0.92	4.6	1.8	1.03	8.27	0.81	6.38	3.62	11.89	4.64	1.04
rd.cr.kh.v2.exp.nc3	2.96	0.09	0.83	0.51	4	1.82	1.03	9.88	1.6	8.94	7.88	17.76	1.99	1.1
rd.cr.kh.v2.exp.nc4	2.96	0.09	0.84	0.68	4.73	2.1	1.03	15.56	2.43	11.01	0.75	16.31	14.81	1.18
rd.cr.kh.v2.exp.nc5	2.94	0.09	0.83	0.52	3.86	2.16	1.03	10.03	1.46	8.55	6.75	16.79	3.28	1.1
rd.cr.kh.v3.pol.nc2	2.33	0.06	0.67	0.6	3.05	1.01	0.98	6.59	0.43	4.66	0.06	6.65	6.53	1
rd.cr.kh.v3.pol.nc3	2.34	0.06	0.65	0.26	2.76	1.76	0.98	6.03	0.5	4.98	3.65	9.68	2.38	1.04
rd.cr.kh.v3.pol.nc4	2.36	0.06	0.66	0.22	2.68	1.76	0.98	9.32	0.87	6.6	0.6	9.92	8.72	1.09
rd.cr.kh.v3.pol.nc5	2.38	0.06	0.66	0.05	2.44	2.26	0.98	9.33	1.02	7.14	3.84	13.17	5.5	1.09
rd.cr.kh.v3.sin.nc2	2.32	0.06	0.67	0.63	2.97	0.93	0.98	4.47	0.23	3.37	1.65	6.12	2.82	1.02
rd.cr.kh.v3.sin.nc3	2.35	0.06	0.66	0.26	2.74	1.79	0.98	1.28	0.03	1.25	1.22	2.5	0.07	1.01
rd.cr.kh.v3.sin.nc4	2.36	0.06	0.66	0.28	2.78	1.56	0.98	10.8	1.17	7.64	0.06	10.87	10.74	1.11
rd.cr.kh.v3.sin.nc5	2.38	0.06	0.66	0.06	2.46	2.23	0.98	9.72	1.07	7.33	3.6	13.32	6.12	1.1
rd.cr.kh.v3.tnh.nc2	2.31	0.06	0.66	0.51	2.99	1.19	0.98	2.68	0.1	2.22	1.65	4.32	1.03	1.03
rd.cr.kh.v3.tnh.nc3	2.35	0.06	0.66	0.28	2.77	1.74	0.98	1.9	0.04	1.42	0.66	2.55	1.24	1.01
rd.cr.kh.v3.tnh.nc4	2.35	0.06	0.66	0.33	2.86	1.4	0.98	11.51	1.33	8.15	0.49	12.01	11.02	1.12
rd.cr.kh.v3.tnh.nc5	2.37	0.06	0.66	0.12	2.51	2.03	0.98	7.79	0.63	5.62	1.53	9.33	6.26	1.08
rd.cr.kh.v3.exp.nc2	2.27	0.06	0.68	0.91	3.24	0.44	0.98	6.97	0.49	4.93	0.16	7.13	6.81	1
rd.cr.kh.v3.exp.nc3	2.32	0.06	0.66	0.47	3.25	1.16	0.98	6.83	0.77	6.2	5.51	12.34	1.31	1.06
rd.cr.kh.v3.exp.nc4	2.33	0.06	0.66	0.52	3.07	0.93	0.98	10.82	1.19	7.71	1.35	12.16	9.47	1.11
rd.cr.kh.v3.exp.nc5	2.36	0.06	0.66	0.26	2.85	1.73	0.98	6.51	0.62	5.55	4.37	10.89	2.14	1.07
rd.cr.kh.v4.pol.nc2	2.39	0.06	0.68	0.52	3.47	1.35	0.98	6.84	0.47	4.84	0.24	7.08	6.6	1
rd.cr.kh.v4.pol.nc3	2.4	0.06	0.67	0.17	2.63	1.99	0.98	6.22	0.51	5.04	3.48	9.7	2.74	1.03
rd.cr.kh.v4.pol.nc4	2.41	0.06	0.67	0.25	2.84	1.96	0.98	9.22	0.86	6.55	0.91	10.12	8.31	1.09
rd.cr.kh.v4.pol.nc5	2.42	0.06	0.68	0.28	3.13	1.95	0.98	9.51	1.05	7.26	3.86	13.37	5.65	1.1

Table c: continued

cr = cluster wise regression, kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics: mn error	ms error	rms error	error std	max error	min error	slope	prediction statistics: mn error	ms error	rms error	error std	max error	min error	slope
rd.cr.kh.v4.sin.nc2	2.38	0.06	0.68	0.52	3.33	1.26	0.98	4.67	0.24	3.47	1.51	6.18	3.17	1.02
rd.cr.kh.v4.sin.nc3	2.42	0.06	0.68	0.31	2.95	2.02	0.98	1.2	0.02	1.11	1.02	2.21	0.18	1.01
rd.cr.kh.v4.sin.nc4	2.41	0.06	0.67	0.27	2.85	1.97	0.98	10.74	1.15	7.59	0.23	10.97	10.51	1.11
rd.cr.kh.v4.sin.nc5	2.42	0.06	0.68	0.27	3.13	1.96	0.98	9.9	1.11	7.45	3.62	13.52	6.28	1.1
rd.cr.kh.v4.tnh.nc2	2.38	0.06	0.67	0.33	3	1.69	0.98	2.58	0.1	2.27	1.92	4.5	0.65	1.03
rd.cr.kh.v4.tnh.nc3	2.42	0.06	0.68	0.31	2.95	2.02	0.98	1.71	0.03	1.27	0.55	2.27	1.16	1.01
rd.cr.kh.v4.tnh.nc4	2.4	0.06	0.67	0.29	2.87	1.98	0.98	11.47	1.32	8.11	0.21	11.68	11.26	1.11
rd.cr.kh.v4.tnh.nc5	2.42	0.06	0.68	0.26	2.88	1.85	0.98	7.91	0.65	5.69	1.49	9.4	6.42	1.08
rd.cr.kh.v4.exp.nc2	2.33	0.06	0.68	0.72	3.41	0.76	0.98	7.23	0.52	5.12	0.02	7.26	7.21	1
rd.cr.kh.v4.exp.nc3	2.36	0.06	0.66	0.24	2.77	1.74	0.98	7.04	0.79	6.27	5.4	12.44	1.65	1.05
rd.cr.kh.v4.exp.nc4	2.38	0.06	0.67	0.36	3.03	1.54	0.98	10.65	1.14	7.56	0.99	11.63	9.66	1.11
rd.cr.kh.v4.exp.nc5	2.4	0.06	0.67	0.14	2.64	2.2	0.98	6.29	0.62	5.56	4.71	11	1.57	1.06
rd.cr.kh.v5.pol.nc2	0.46	0	0.17	0.41	1.39	0.03	1	6.75	0.51	5.05	2.36	9.11	4.38	1.02
rd.cr.kh.v5.pol.nc3	0.2	0	0.08	0.18	0.62	0.02	1	6.17	0.76	6.17	6.16	12.34	0.01	1.06
rd.cr.kh.v5.pol.nc4	0.15	0	0.06	0.17	0.63	0.01	1	11.87	1.44	8.47	8.62	12.58	11.35	1.16
rd.cr.kh.v5.pol.nc5	0.05	0	0.02	0.02	0.11	0	1	11.99	1.59	8.92	3.93	15.92	8.06	1.12
rd.cr.kh.v5.sin.nc2	0.46	0	0.18	0.45	1.47	0.05	1	4.58	0.38	4.35	4.11	8.69	0.47	1.04
rd.cr.kh.v5.sin.nc3	0.2	0	0.07	0.17	0.59	0.03	1	3.74	0.16	2.79	1.24	4.99	2.5	1.04
rd.cr.kh.v5.sin.nc4	0.19	0	0.08	0.22	0.82	0.01	1	13.49	1.82	9.54	0.08	13.55	13.43	1.13
rd.cr.kh.v5.sin.nc5	0.08	0	0.05	0.03	0.14	0.02	1	12.38	1.67	9.13	3.68	16.06	8.7	1.12
rd.cr.kh.v5.tnh.nc2	0.42	0	0.15	0.32	1.21	0.04	1	5.17	0.3	3.84	1.69	6.85	3.48	1.05
rd.cr.kh.v5.tnh.nc3	0.21	0	0.08	0.19	0.65	0.03	1	3.1	0.13	2.59	1.94	5.04	1.15	1.03
rd.cr.kh.v5.tnh.nc4	0.22	0	0.09	0.26	0.99	0.01	1	14.22	2.02	10.06	0.5	14.72	13.72	1.14
rd.cr.kh.v5.tnh.nc5	0.09	0	0.03	0.08	0.35	0.02	1	10.41	1.11	7.44	1.57	11.98	8.84	1.1
rd.cr.kh.v5.exp.nc2	0.76	0.01	0.26	0.56	1.98	0.01	1	7.14	0.58	5.37	2.59	9.73	4.55	1.03
rd.cr.kh.v5.exp.nc3	0.34	0	0.13	0.34	1.24	0.02	1	8.07	1.14	7.55	6.99	15.06	1.08	1.08
rd.cr.kh.v5.exp.nc4	0.36	0	0.15	0.4	1.48	0.02	1	13.5	1.84	9.6	1.38	14.88	12.12	1.14
rd.cr.kh.v5.exp.nc5	0.2	0	0.07	0.18	0.65	0.02	1	9.1	1.03	7.17	4.48	13.58	4.62	1.09
rd.cr.at.v1.pol.nc5	1.64	0.04	0.54	1.05	3.8	0.1	1.02	10.87	2.17	10.43	0.06	20.83	0.01	1.11
rd.cr.at.v1.sin.nc5	1.85	0.05	0.61	1.10	0.85	0.00	1.03	37.03	7.08	10.08	1.3	33.14	33.73	0.86
rd.cr.at.v1.tnh.nc5	2.43	0.08	0.78	1.3	4.32	0.21	1.02	14.11	[illegible]	[illegible]	8.32	23.73	[illegible]	[illegible]
rd.cr.at.v1.exp.nc5	1.52	0.02	[illegible]	0.04	1.63	1.46	1.02	56.38	50.81	50.41	43.62	100	12.76	0.56
rd.cr.at.v2.pol.nc5	2.99	0.1	0.88	1.05	5.13	1.3	1.03	12.81	2.68	11.57	10.17	22.98	2.64	1.13
rd.cr.at.v2.sin.nc5	3.04	0.11	0.93	1.39	5.17	0.32	1.03	29.9	9.87	21.3	3.69	33.59	26.21	0.96

Table C: continued

cr = cluster wise regression, kh=SOM clustering, at=A.R.T.2, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
rd.cr.at.v2.tnh.nc5	3.36	0.14	1.05	1.75	5.64	0.06	1.03	15.12	3.52	13.27	11.11	26.23	4.02	1.11
rd.cr.at.v2.exp.nc5	2.88	0.08	0.8	0.04	3.01	2.82	1.03	56.75	50.91	50.45	43.25	100	13.5	0.57
rd.cr.at.v3.pol.nc5	2.37	0.06	0.66	0.09	2.54	2.22	0.98	6.2	0.39	4.43	0.84	7.05	5.36	1.01
rd.cr.at.v3.sin.nc5	2.37	0.06	0.66	0.11	2.59	2.18	0.98	5.49	0.32	4.03	1.53	7.02	3.95	1.02
rd.cr.at.v3.tnh.nc5	2.36	0.06	0.66	0.14	2.52	2.07	0.98	5.78	0.34	4.15	0.97	6.75	4.81	1.01
rd.cr.at.v3.exp.nc5	2.37	0.06	0.66	0.01	2.38	2.35	0.98	55.33	50.57	50.28	44.07	100	10.07	0.55
rd.cr.at.v4.pol.nc5	2.43	0.06	0.68	0.34	3.33	1.87	0.98	6.38	0.41	4.55	8.71	7.13	5.64	1.01
rd.cr.at.v4.sin.nc5	2.42	0.06	0.68	0.33	3.3	1.89	0.98	5.64	0.34	4.12	1.46	7.1	4.18	1.01
rd.cr.at.v4.tnh.nc5	2.43	0.06	0.68	0.29	2.86	1.73	0.98	6.02	0.37	4.29	0.81	6.83	5.21	1.01
rd.cr.at.v4.exp.nc5	2.37	0.06	0.66	0.05	2.53	2.26	0.98	55.39	50.58	50.29	44.61	100	10.77	0.55
rd.cr.at.v5.pol.nc5	0.07	0	0.02	0.05	0.18	0.01	1	6.35	0.51	5.06	3.29	9.64	3.06	1.03
rd.cr.at.v5.sin.nc5	0.09	0	0.03	0.06	0.22	0	1	5.62	0.48	4.88	4	9.62	1.63	1.04
rd.cr.at.v5.tnh.nc5	0.12	0	0.04	0.09	0.3	0	1	5.92	0.47	4.84	3.42	9.34	2.51	1.03
rd.cr.at.v5.exp.nc5	0	0	0	0	0.01	0	1	56.68	50.89	50.44	43.32	100	13.35	0.57
rd.cr.fa.v1.pol.nc5	2.26	0.08	0.78	1.69	6.6	0.26	1.02	51.4	50.04	50.02	48.6	100	2.79	0.49
rd.cr.fa.v1.sin.nc5	2.31	0.08	0.78	1.62	7.06	0.73	1.02	60.76	52.32	51.14	39.24	100	21.52	0.39
rd.cr.fa.v1.tnh.nc5	2.36	0.08	0.81	1.71	7.45	0.83	1.02	58.54	51.46	50.72	41.46	100	17.07	0.41
rd.cr.fa.v1.exp.nc5	2.6	0.09	0.84	1.54	5.29	0.03	1.02	64.31	54.1	52.01	35.69	100	28.62	0.64
rd.cr.fa.v2.pol.nc5	3.28	0.15	1.06	1.96	7.83	0.59	1.03	50.93	50.02	50.01	49.07	100	1.87	0.49
rd.cr.fa.v2.sin.nc5	3.34	0.15	1.06	1.87	8.32	0.69	1.03	60.68	52.28	51.13	39.32	100	21.36	0.39
rd.cr.fa.v2.tnh.nc5	3.35	0.15	1.08	1.99	8.71	0.43	1.03	58.37	51.4	50.7	41.63	100	16.74	0.42
rd.cr.fa.v2.exp.nc5	3.42	0.16	1.11	2.1	6.75	0.56	1.03	64.92	54.45	52.18	35.08	100	29.84	0.65
rd.cr.fa.v3.pol.nc5	2.34	0.06	0.66	0.29	2.83	1.81	0.98	52.29	50.1	50.05	47.71	100	4.58	0.48
rd.cr.fa.v3.sin.nc5	2.32	0.06	0.67	0.62	2.87	0.88	0.98	51.41	50.04	50.02	48.59	100	2.82	0.49
rd.cr.fa.v3.tnh.nc5	2.32	0.06	0.67	0.63	3.04	0.63	0.98	50.71	50.01	50.01	49.29	100	1.42	0.49
rd.cr.fa.v3.exp.nc5	2.55	0.09	0.82	1.52	4.77	0.21	0.98	61.98	52.87	51.41	38.02	100	23.98	0.62
rd.cr.fa.v4.pol.nc5	2.41	0.06	0.67	0.22	2.72	1.97	0.98	52.49	50.12	50.06	47.51	100	4.98	0.48
rd.cr.fa.v4.sin.nc5	2.38	0.06	0.68	0.52	3.33	1.26	0.98	51.58	50.05	50.03	48.42	100	3.17	0.48
rd.cr.fa.v4.tnh.nc5	2.38	0.06	0.68	0.51	3.25	1.26	0.98	50.86	50.01	50.01	49.14	100	1.73	0.49
rd.cr.fa.v4.exp.nc5	2.51	0.08	0.81	1.47	4.62	0.36	0.98	62.07	52.91	51.44	37.93	100	24.14	0.62
rd.cr.fa.v5.pol.nc5	0.23	0	0.08	0.18	0.57	0.01	1	51.13	50.03	50.01	48.87	100	2.27	0.49
rd.cr.fa.v5.sin.nc5	0.44	0	0.18	0.46	1.47	0.08	1	50.23	50	50	49.77	100	0.47	0.5
rd.cr.fa.v5.tnh.nc5	0.43	0	0.18	0.48	1.48	0.02	1	50.49	50	50	49.51	100	0.98	0.5
rd.cr.fa.v5.exp.nc5	1.79	0.04	0.58	1.05	3.76	0.41	1	63.48	53.63	51.79	36.52	100	26.96	0.63

Table C: continued

cr = cluster wise regression, at=A.R.T.2 clustering, fa=fuzzy A.R.T.2 clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, rd = data prepared using mean with SAIL R&D 's experience, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modelling	training statistics: mn error	ms error	rms error	error std	max error	min error	slope	prediction statistics: mn error	ms error	rms error	error std	max error	min error	slope
rd.oclstr.fc.nc1.e1	0.34	0	0.11	0.22	0.81	0.13	1	75.82	58.97	54.3	12.19	88.01	63.62	1.12
rd.oclstr.fc.nc1.e2	4.05	0.24	1.35	2.71	11.12	0.29	1	15.87	2.66	11.54	3.8	19.67	12.07	1.1[illegible]
rd.oclstr.fc.nc1.e3	7.25	0.77	2.43	4.92	18.65	0.15	1.01	10.12	1.03	7.16	0.3	10.43	9.82	1.[illegible]
rd.oclstr.fc.nc1.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0[illegible]
rd.oclstr.fc.nc1.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0[illegible]
rd.oclstr.fc.nc2.e1	1.76	0.05	0.62	1.37	5.55	0.17	1	13.14	1.95	9.87	4.72	17.86	8.42	1.0[illegible]
rd.oclstr.fc.nc2.e2	2.08	0.06	0.7	1.42	5.57	0.39	1	14.8	2.21	10.51	1.38	16.18	13.42	1.0[illegible]
rd.oclstr.fc.nc2.e3	5.84	0.63	2.2	5.37	18.2	0.28	1.01	4.81	0.36	4.24	3.58	8.38	1.23	1.0[illegible]
rd.oclstr.fc.nc2.e4	13.97	2.48	4.37	7.27	34.34	3.74	1.02	9.49	1.42	8.43	7.22	16.71	2.27	1.0[illegible]
rd.oclstr.fc.nc2.e5	13.97	2.48	4.37	7.27	34.34	3.74	1.02	9.49	1.42	8.43	7.22	16.71	2.27	1.0[illegible]
rd.oclstr.fc.nc3.e1	1.28	0.03	0.45	0.99	3.7	0.05	1	41.06	29.6	38.47	35.7	76.76	5.37	0.6[illegible]
rd.oclstr.fc.nc3.e2	3	0.19	1.21	3.16	12.18	0.05	1	31.7	16.98	29.14	26.32	58.03	5.38	0.7[illegible]
rd.oclstr.fc.nc3.e3	5.25	0.47	1.91	4.43	14.45	0.2	1	32.3	16.97	29.13	25.58	57.87	8.72	0.7[illegible]
rd.oclstr.fc.nc3.e4	6.74	0.75	2.4	5.42	19.42	0.37	1	31.1	16.85	29.02	26.79	57.89	4.31	0.7[illegible]
rd.oclstr.fc.nc3.e5	6.74	0.75	2.4	5.42	19.42	0.37	1	31.1	16.85	29.02	26.79	57.89	4.31	0.7[illegible]
rd.oclstr.fc.nc4.e1	0.76	0.01	0.32	0.87	2.6	0	1	29.58	9.01	21.22	5.07	34.65	24.51	1.3[illegible]
rd.oclstr.fc.nc4.e2	2.52	0.1	0.88	1.91	6.38	0.12	1	30.63	9.75	22.08	6.05	36.68	24.59	1.31
rd.oclstr.fc.nc4.e3	4.01	0.49	1.94	5.73	20.41	0.13	0.99	19.45	4.05	14.23	5.14	24.59	14.31	1.19
rd.oclstr.fc.nc4.e4	6.46	0.83	2.52	6.41	20.37	0.2	1	13.86	1.92	9.81	0.53	14.39	13.32	1.14
rd.oclstr.fc.nc4.e5	6.46	0.83	2.52	6.41	20.37	0.2	1	13.86	1.92	9.81	0.53	14.39	13.32	1.14
rd.oclstr.fc.nc5.e1	0.66	0.01	0.24	0.55	1.69	0	1	278.64	1384.79	263.13	246.65	525.29	32	3.79
rd.oclstr.fc.nc5.e2	4.08	0.3	1.53	3.72	12.39	0	1	266.78	1380	262.68	258.51	525.29	8.27	3.67
rd.oclstr.fc.nc5.e3	5.61	0.5	1.96	4.29	12.52	0	1	266.67	1380.01	262.68	258.63	525.3	8.03	3.67
rd.oclstr.fc.nc5.e4	5.61	0.5	1.96	4.29	12.52	0	1	266.67	1380.01	262.68	258.63	525.3	8.03	3.67
rd.oclstr.fc.nc5.e5	8.19	1.05	2.85	6.18	21.45	0	1.01	263.1	1379.73	262.65	262.2	525.3	0.9	3.62
rd.oclstr.km.nc1.e1	0.34	0	0.11	0.22	0.81	0.13	1	75.82	58.97	54.3	12.19	88.01	63.62	1.12
rd.oclstr.km.nc1.e2	4.05	0.24	1.35	2.71	11.12	0.29	1	15.87	2.66	11.54	3.8	19.67	12.07	1.16
rd.oclstr.km.nc1.e3	7.25	0.77	2.43	4.92	18.65	0.15	1.01	10.12	1.03	7.16	0.3	10.43	9.82	1.1
rd.oclstr.km.nc1.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.km.nc1.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.km.nc2.e1	1.29	0.04	0.57	1.61	5.3	0.01	1	6.08	0.45	4.72	2.74	8.82	3.34	0.94
rd.oclstr.km.nc2.e2	4.68	0.34	1.61	3.43	14.24	0.36	1	3.31	0.11	2.34	0.07	3.37	3.24	1
rd.oclstr.km.nc2.e3	5.28	0.54	2.03	5.06	18.93	0.36	1	5.29	0.32	3.98	1.92	7.22	3.37	1.02
rd.oclstr.km.nc2.e4	11.92	2	3.92	7.58	24.15	0.69	1.02	8.54	0.75	6.11	1.32	9.86	7.22	1.09

Table C: continued

oclstr=ortho-clustering, fc = fuzzy c-means clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)
nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modeling	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
rd.oclstr.km.nc2.e5	11.92	2	3.92	7.58	24.15	0.69	1.02	8.54	0.75	6.11	1.32	9.86	7.22	1.0
rd.oclstr.km.nc3.e1	1.61	0.04	0.54	1.07	4.12	0.46	1	12.75	2.64	11.5	10.1	22.85	2.65	0.8
rd.oclstr.km.nc3.e2	3.37	0.18	1.17	2.56	8.08	0.21	1	9.03	0.89	6.68	2.76	11.79	6.27	0.9
rd.oclstr.km.nc3.e3	5.32	0.4	1.74	3.35	14.68	1.22	1	10.19	1.06	7.29	1.6	11.79	8.58	0
rd.oclstr.km.nc3.e4	7.96	1.09	2.9	6.79	23.84	0.83	1.01	17.03	3.17	12.6	5.23	22.26	11.8	1.0
rd.oclstr.km.nc3.e5	7.96	1.09	2.9	6.79	23.84	0.83	1.01	17.03	3.17	12.6	5.23	22.26	11.8	1.0
rd.oclstr.km.nc4.e1	0.6	0.01	0.21	0.48	1.84	0.05	1	62.99	42.13	45.89	15.64	78.63	47.36	0.8
rd.oclstr.km.nc4.e2	1.68	0.07	0.71	1.94	6.87	0.04	1	65.26	45.31	47.6	16.51	81.77	48.75	0.8
rd.oclstr.km.nc4.e3	3.53	0.32	1.56	4.4	15.35	0.04	1	65.03	45.07	47.47	16.65	81.69	48.38	0.8
rd.oclstr.km.nc4.e4	5.82	0.71	2.33	6.05	20.37	0.03	1	53.71	29.11	38.15	5.17	58.88	48.54	0.9
rd.oclstr.km.nc4.e5	5.82	0.71	2.33	6.05	20.37	0.03	1	53.71	29.11	38.15	5.17	58.88	48.54	0.9
rd.oclstr.km.nc5.e1	0.47	0.01	0.23	0.68	2.52	0	1	32.54	13.2	25.69	16.17	48.7	16.37	1.3
rd.oclstr.km.nc5.e2	3.22	0.14	1.05	1.98	7.26	0	1	34.22	16.46	28.69	21.79	56.01	12.44	1.3
rd.oclstr.km.nc5.e3	3.65	0.22	1.29	2.89	10.61	0	1	34.02	16.29	28.54	21.71	55.73	12.31	1.3
rd.oclstr.km.nc5.e4	6.32	0.66	2.25	5.06	19.08	0	1.02	34.03	16.3	28.55	21.72	55.75	12.31	1.3
rd.oclstr.km.nc5.e5	10.01	2.3	4.21	11.41	40.05	0	1.01	34.05	16.32	28.56	21.73	55.78	12.32	1.3
rd.oclstr.kh.nc1.e1	0.34	0	0.11	0.22	0.81	0.13	1	75.82	58.97	54.3	12.19	88.01	63.62	1.1
rd.oclstr.kh.nc1.e2	4.05	0.24	1.35	2.71	11.12	0.29	1	15.87	2.66	11.54	3.8	19.67	12.07	1.1
rd.oclstr.kh.nc1.e3	7.25	0.77	2.43	4.92	18.65	0.15	1.01	10.12	1.03	7.16	0.3	10.43	9.82	1.
rd.oclstr.kh.nc1.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0
rd.oclstr.kh.nc1.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0
rd.oclstr.kh.nc2.e1	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc2.e2	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc2.e3	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc2.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0
rd.oclstr.kh.nc2.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0
rd.oclstr.kh.nc3.e1	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc3.e2	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc3.e3	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc3.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0
rd.oclstr.kh.nc3.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.0
rd.oclstr.kh.nc4.e1	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc4.e2	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6
rd.oclstr.kh.nc4.e3	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.6

Table C: conitinued

oclstr=ortho-clustering, kh=SOM clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)

nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error

rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modeling	training statistics mn error	ms error	rms error	error std	max error	min error	slope	prediction statistics mn error	ms error	rms error	error std	max error	min error	slope
rd.oclstr.kh.nc4.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.kh.nc4.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.kh nc5.e1	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.68
rd.oclstr.kh.nc5.e2	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.68
rd.oclstr.kh.nc5.e3	124.31	257.22	44.48	101.34	344.06	17.53	1.69	100.31	146.3	85.53	67.6	167.9	32.71	1.68
rd.oclstr.kh.nc5.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.kh.nc5.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.at.nc5.e1	0.34	0	0.11	0.22	0.81	0.13	1	75.82	58.97	54.3	12.19	88.01	63.62	1.12
rd.oclstr.at.nc5.e2	4.05	0.24	1.35	2.71	11.12	0.29	1	15.87	2.66	11.54	3.8	19.67	12.07	1.16
rd.oclstr.at.nc5.e3	7.25	0.77	2.43	4.92	18.65	0.15	1.01	10.12	1.03	7.16	0.3	10.43	9.82	1.1
rd.oclstr.at.nc5.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.at.nc5.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.oclstr.fa.nc5.e1	0.34	0	0.11	0.22	0.81	0.13	1	75.82	58.97	54.3	12.19	88.01	63.62	1.12
rd.oclstr.fa.nc5.e2	4.05	0.24	1.35	2.71	11.12	0.29	1	15.87	2.66	11.54	3.8	19.67	12.07	1.16
rd.oclstr.fa.nc5.e3	7.25	0.77	2.43	4.92	18.65	0.15	1.01	10.12	1.03	7.16	0.3	10.43	9.82	1.1
rd.oclstr.fa.nc5.e4	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.08
rd.oclstr.fa.nc5.e5	11.79	2.11	4.03	8.49	24.87	0.53	1.02	6.48	0.55	5.25	3.63	10.11	2.85	1.06
rd.autregrma.v1.pol	6.87	0.61	2.26	3.73	13.69	1.21	0.97	32.58	16.85	29.03	24.97	57.55	7.61	1.33
rd.autregrma.v1.sin	6.14	0.58	2.2	4.49	15.38	0.01	0.97	69.3	56.26	53.04	28.71	98.01	40.59	1.69
rd.autregrma.v1.tnh	5.39	0.5	2.04	4.58	14.92	0.16	0.97	87.14	86.12	65.62	31.9	119.05	55.24	1.87
rd.autregrma.v1.exp	2.34	0.06	0.71	0.7	3.88	1.32	0.98	83.96	72.41	60.17	13.86	97.82	70.1	0.16
rd.autregrma.v2.pol	8.46	1.08	2.99	6	21.15	2.69	1.01	25.59	11.33	23.8	21.86	47.45	3.73	0.74
rd.autregrma.v2.sin	8.24	1.06	2.98	6.21	20.06	0.3	1.01	19.93	4.51	15.02	7.35	27.28	12.58	0.93
rd.autregrma.v2.tnh	8.04	0.97	2.85	5.72	20.1	0.51	1.01	20.56	4.64	15.23	6.4	26.96	14.17	1.06
rd.autregrma.v2.exp	1.65	0.04	0.59	1.22	3.83	0.22	1.02	75.48	57.64	53.69	8.23	83.71	67.24	0.25
rd.autregrma.v3.pol	2.35	0.07	0.74	1.03	4.34	1.06	0.98	83.02	73.77	60.73	22.04	105.06	60.97	0.17
rd.autregrma.v3.sin	2.37	0.07	0.75	1.08	4.51	0.86	0.98	46.91	26.71	36.54	21.67	68.58	25.24	0.53
rd.autregrma.v3.tnh	2.37	0.07	0.74	0.99	4.28	0.94	0.98	29.43	10.87	23.31	14.87	44.3	14.56	0.71
rd.autregrma.v3.exp	2.36	0.06	0.68	0.22	2.65	2.02	0.98	63.9	41.87	45.76	10.19	74.09	53.71	0.36
rd.autregrma.v4.pol	2.34	0.07	0.74	1.05	4.43	0.44	0.98	84.62	76.77	61.96	22.74	107.36	61.87	0.15
rd.autregrma.v4.sin	2.35	0.07	0.75	1.09	4.59	0.22	0.98	47.64	27.69	37.21	22.36	70	25.28	0.52
rd.autregrma.v4.tnh	2.36	0.07	0.74	1	4.36	0.31	0.98	29.73	11.21	23.67	15.39	45.12	14.33	0.7
rd.autregrma.v4.exp	2.35	0.06	0.7	0.58	3.25	1.22	0.98	65.04	43.36	46.56	10.28	75.31	54.76	0.35
rd.autregrma.v5.pol	0.91	0.01	0.31	0.54	2.02	0.02	1	82.6	73.33	60.55	22.58	105.18	60.02	0.17

Table C: continued

oclstr=ortho-clustering, kh=SOM clustering,at=ART2, fa=fuzzy ART, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)
autregrma = ARMA, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic, exponential modeling functions
nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.simplregr.v1.pol	4.6	0.42	1.79	4.55	16.8	0.09	1.02	42.34	21.73	32.96	19.5	61.84	22.83	1.42
pca.simplregr.v1.sin	4.39	0.36	1.67	4.11	13.73	0.28	1.02	37.26	15.06	27.44	10.85	48.11	26.41	1.37
pca.simplregr.v1.tnh	4.23	0.31	1.55	3.64	12.32	0.62	1.02	34.81	12.6	25.1	6.94	41.75	27.87	1.35
pca.simplregr.v1.exp	1.79	0.05	0.61	1.3	4.34	0.08	1.02	51.01	44.22	47.02	42.66	93.67	8.34	1.51
pca.simplregr.v2.pol	5.09	0.5	1.97	4.93	18.04	0.43	1.04	44.87	23.84	34.52	19.25	64.12	25.61	1.45
pca.simplregr.v2.sin	4.96	0.44	1.85	4.46	15.05	0.76	1.04	39.55	16.73	28.92	10.43	49.98	29.12	1.4
pca.simplregr.v2.tnh	4.73	0.39	1.73	4.08	13.57	0.74	1.04	37	14.12	26.57	6.51	43.51	30.5	1.37
pca.simplregr.v2.exp	3.09	0.12	0.94	1.41	5.65	0.78	1.03	53.67	47.28	48.62	42.99	96.66	10.68	1.54
pca.simplregr.v3.pol	2.35	0.06	0.68	0.74	3.34	0.84	0.98	55.1	39.98	44.71	31.02	86.12	24.08	1.55
pca.simplregr.v3.sin	2.38	0.07	0.72	1.06	3.76	0.36	0.98	47.46	23.51	34.28	9.9	57.36	37.56	1.47
pca.simplregr.v3.tnh	2.43	0.07	0.74	1.1	4.12	0.7	0.98	33.57	11.28	23.75	0.96	34.53	32.61	1.34
pca.simplregr.v3.exp	2.38	0.06	0.67	0.28	2.86	1.89	0.98	42.62	35.74	42.27	41.92	84.54	0.7	1.42
pca.simplregr.v4.pol	2.43	0.06	0.7	0.72	3.44	1.16	0.98	56.31	41.66	45.64	31.55	87.86	24.75	1.56
pca.simplregr.v4.sin	2.41	0.07	0.74	1.12	4.24	0.07	0.98	48.49	24.49	35	9.91	58.4	38.57	1.48
pca.simplregr.v4.tnh	2.46	0.07	0.75	1.15	4.63	0.41	0.98	34.25	11.74	24.23	0.75	35.01	33.5	1.34
pca.simplregr.v4.exp	2.46	0.06	0.69	0.42	3.38	1.81	0.98	43.44	37.19	43.12	42.81	86.25	0.63	1.43
pca.simplregr.v5.pol	0.64	0.01	0.21	0.41	1.6	0.11	1	58.91	44.8	47.33	31.78	90.69	27.12	1.59
pca.simplregr.v5.sin	0.07	0.01	0.34	0.72	2.83	0.02	1	51.09	27.13	36.83	10.14	61.23	40.94	1.51
pca.simplregr.v5.tnh	1.08	0.02	0.37	0.8	3.17	0.1	1	36.85	13.59	26.07	0.98	37.84	35.87	1.37
pca.simplregr.v5.exp	0.23	0	0.08	0.18	0.52	0	1	45.41	39.69	44.55	43.67	89.08	1.74	1.45
pca.cr.fc.v1.pol.nc2	1.95	0.07	0.76	1.92	6.75	0.01	1.02	48.91	30.97	39.35	26.55	75.46	22.37	1.49
pca.cr.fc.v1.pol.nc3	1.76	0.04	0.56	1.02	4.13	0.54	1.02	22.32	5.06	15.9	2.73	25.06	19.59	1.22
pca.cr.fc.v1.pol.nc4	1.65	0.03	0.51	0.82	2.86	0.1	1.02	14.68	3.61	13.44	12.09	26.76	2.59	1.15
pca.cr.fc.v1.pol.nc5	1.63	0.03	0.5	0.79	3.08	0.31	1.02	1.51	0.03	1.31	1.08	2.59	0.43	1.02
pca.cr.fc.v1.sin.nc2	1.69	0.04	0.56	1.13	3.9	0.02	1.02	47.41	25.75	35.88	18.08	65.49	29.33	1.47
pca.cr.fc.v1.sin.nc3	1.79	0.04	0.59	1.13	4.21	0.57	1.02	25.54	6.58	18.14	2.49	28.03	23.04	1.26
pca.cr.fc.v1.sin.nc4	1.66	0.04	0.53	0.9	3.02	0.01	1.02	6.88	0.86	6.55	6.19	13.08	0.69	1.07
pca.cr.fc.v1.sin.nc5	1.66	0.04	0.52	0.9	3.02	0.01	1.02	6.88	0.86	6.55	6.19	13.08	0.69	1.07
pca.cr.fc.v1.tnh.nc2	2.1	0.06	0.7	1.38	4.92	0.51	1.02	53.24	37.61	43.37	30.44	83.68	22.8	1.53
pca.cr.fc.v1.tnh.nc3	1.81	0.05	0.6	1.21	4.22	0.45	1.02	26.44	7.24	19.02	4.96	31.4	21.48	1.26
pca.cr.fc.v1.tnh.nc4	1.69	0.04	0.54	0.95	3.1	0.11	1.02	7.38	1.09	7.37	7.36	14.74	0.01	1.07
pca.cr.fc.v1.tnh.nc5	1.69	0.04	0.54	0.95	3.1	0.11	1.02	7.38	1.09	7.37	7.36	14.74	0.01	1.07
pca.cr.fc.v1.exp.nc2	1.61	0.03	0.46	0.41	2.23	1.02	1.02	47.97	27.66	37.19	21.54	69.52	26.43	1.48
pca.cr.fc.v1.exp.nc3	1.6	0.03	0.45	0.3	1.96	1.11	1.02	19.44	3.8	13.78	1.34	20.78	18.1	1.19

Table D: performance statistics of all models on problem of estimation of life of converter lining (PCA)

* simplregr = simple rigression, cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.cr.fc.v1.exp.nc4	1.59	0.03	0.45	0.29	1.96	1.11	1.02	17.48	3.32	12.88	5.18	22.66	12.31	1.17
pca.cr.fc.v1.exp.nc5	1.59	0.03	0.45	0.26	1.97	1.11	1.02	16.89	1.21	7.77	1.42	12.31	0.48	1.01
pca.cr.fc.v2.pol.nc2	3.17	0.14	1.05	2.04	8.06	0.83	1.03	53	35.9	42.37	27.93	80.94	25.07	1.53
pca.cr.fc.v2.pol.nc3	3.06	0.11	0.9	1.12	5.43	0.9	1.03	25.09	6.39	17.88	3.17	28.26	21.92	1.25
pca.cr.fc.v2.pol.nc4	3.03	0.1	0.87	0.8	4.2	1.53	1.03	16.48	4.4	14.84	12.99	29.47	3.5	1.16
pca.cr.fc.v2.pol.nc5	3.02	0.1	0.86	0.77	4.42	1.73	1.03	2.51	0.07	1.91	0.98	3.5	1.53	1.03
pca.cr.fc.v2.sin.nc2	3.07	0.11	0.9	1.11	5.25	1.41	1.03	51.48	30.02	38.74	18.74	70.23	32.74	1.51
pca.cr.fc.v2.sin.nc3	3.08	0.11	0.92	1.22	5.51	0.88	1.03	28.53	8.19	20.24	2.29	30.81	26.24	1.29
pca.cr.fc.v2.sin.nc4	3.04	0.1	0.88	0.88	4.36	1.42	1.03	8.43	1.18	7.69	6.89	15.31	1.54	1.08
pca.cr.fc.v2.sin.nc5	3.04	0.1	0.88	0.88	4.36	1.42	1.03	8.43	1.18	7.69	6.89	15.31	1.54	1.08
pca.cr.fc.v2.tnh.nc2	3.15	0.13	1	1.76	6.28	0.08	1.03	58.02	43.89	46.85	31.99	90.01	26.02	1.58
pca.cr.fc.v2.tnh.nc3	3.1	0.11	0.93	1.3	5.53	0.84	1.03	29.5	8.94	21.15	4.88	34.38	24.63	1.3
pca.cr.fc.v2.tnh.nc4	3.06	0.1	0.89	0.95	4.43	1.32	1.03	8.96	1.46	8.55	8.12	17.08	0.84	1.09
pca.cr.fc.v2.tnh.nc5	3.05	0.1	0.89	0.95	4.43	1.32	1.03	8.96	1.46	8.55	8.12	17.08	0.84	1.09
pca.cr.fc.v2.exp.nc2	3	0.09	0.84	0.42	3.62	2.39	1.03	53.99	35.07	41.88	24.35	78.33	29.64	1.54
pca.cr.fc.v2.exp.nc3	2.98	0.09	0.83	0.31	3.35	2.48	1.03	21.87	4.82	15.53	2	23.88	19.87	1.22
pca.cr.fc.v2.exp.nc4	2.98	0.09	0.83	0.29	3.35	2.48	1.03	19.03	4.01	14.16	6.22	25.25	12.81	1.19
pca.cr.fc.v2.exp.nc5	2.97	0.09	0.83	0.28	3.36	2.48	1.03	10.74	1.2	7.73	2.07	12.81	8.67	1.02
pca.cr.fc.v3.pol.nc2	2.39	0.06	0.66	0.14	2.67	2.13	0.98	13.79	1.94	9.84	1.92	15.71	11.87	1.14
pca.cr.fc.v3.pol.nc3	2.4	0.06	0.67	0.09	2.61	2.24	0.98	6.71	0.76	6.17	5.58	12.29	1.13	1.06
pca.cr.fc.v3.pol.nc4	2.4	0.06	0.67	0.06	2.5	2.3	0.98	10.7	1.16	7.62	1.27	11.98	9.43	1.11
pca.cr.fc.v3.pol.nc5	2.4	0.06	0.67	0.06	2.5	2.3	0.98	4.99	0.45	4.73	4.44	9.43	0.56	1.04
pca.cr.fc.v3.sin.nc2	2.39	0.06	0.66	0.11	2.61	2.17	0.98	8.76	1.33	8.15	7.5	16.26	1.26	1.09
pca.cr.fc.v3.sin.nc3	2.39	0.06	0.66	0.1	2.62	2.21	0.98	7.32	0.72	6.01	4.31	11.63	3.01	1.04
pca.cr.fc.v3.sin.nc4	2.4	0.06	0.67	0.07	2.5	2.29	0.98	3.99	0.28	3.74	3.47	7.46	0.52	1.04
pca.cr.fc.v3.sin.nc5	2.4	0.06	0.67	0.07	2.5	2.29	0.98	3.99	0.28	3.74	3.47	7.46	0.52	1.04
pca.cr.fc.v3.tnh.nc2	2.39	0.06	0.66	0.1	2.59	2.18	0.98	9.53	1.4	8.36	6.99	16.52	2.54	1.07
pca.cr.fc.v3.tnh.nc3	2.39	0.06	0.66	0.11	2.62	2.19	0.98	7.38	0.69	5.87	3.79	11.17	3.58	1.04
pca.cr.fc.v3.tnh.nc4	2.4	0.06	0.67	0.08	2.52	2.27	0.98	3.58	0.21	3.28	2.94	6.52	0.65	1.04
pca.cr.fc.v3.tnh.nc5	2.4	0.06	0.67	0.08	2.52	2.27	0.98	3.58	0.21	3.28	2.94	6.52	0.65	1.04
pca.cr.fc.v3.exp.nc2	2.4	0.06	0.66	0.04	2.48	2.32	0.98	18.04	3.7	13.61	6.69	24.73	11.35	1.18
pca.cr.fc.v3.exp.nc3	2.4	0.06	0.66	0.03	2.46	2.35	0.98	9.53	1.08	7.35	4.13	13.66	5.41	1.1
pca.cr.fc.v3.exp.nc4	2.4	0.06	0.66	0.02	2.43	2.36	0.98	13.64	1.86	9.65	0.41	14.05	13.22	1.14
pca.cr.fc.v3.exp.nc5	2.4	0.06	0.66	0.02	2.42	2.36	0.98	12.2	1.5	8.66	1.02	13.22	11.18	1.01

Table D: continued

* simplregr = simple rigression, cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics: mn error	ms error	rms error	error std	max error	min error	slope	prediction statistics: mn error	ms error	rms error	error std	max error	min error	slope
pca.cr.fc.v4.pol.nc2	2.47	0.06	0.69	0.34	2.97	1.66	0.98	14	1.99	9.98	1.79	15.8	12.21	1.14
pca.cr.fc.v4.pol.nc3	2.46	0.06	0.69	0.35	3.16	1.76	0.98	6.81	0.78	6.24	5.62	12.42	1.19	1.06
pca.cr.fc.v4.pol.nc4	2.47	0.06	0.69	0.35	3.16	1.76	0.98	10.86	1.19	7.73	1.26	12.12	9.6	1.11
pca.cr.fc.v4.pol.nc5	2.47	0.06	0.69	0.35	3.16	1.76	0.98	5.23	0.46	4.82	4.37	9.6	8.88	1.04
pca.cr.fc.v4.sin.nc2	2.46	0.06	0.69	0.32	2.88	1.63	0.98	8.85	1.36	8.24	7.58	18.43	1.27	1.09
pca.cr.fc.v4.sin.nc3	2.46	0.06	0.69	0.34	3.15	1.78	0.98	7.43	0.74	6.08	4.32	11.75	3.12	1.04
pca.cr.fc.v4.sin.nc4	2.47	0.06	0.69	0.34	3.06	1.73	0.98	3.98	0.29	3.79	3.6	7.58	0.38	1.04
pca.cr.fc.v4.sin.nc5	2.47	0.06	0.69	0.34	3.15	1.78	0.98	3.98	0.29	3.79	3.6	7.58	0.38	1.04
pca.cr.fc.v4.tnh.nc2	2.46	0.06	0.69	0.3	2.86	1.64	0.98	9.68	1.43	8.46	7.03	16.71	2.66	1.07
pca.cr.fc.v4.tnh.nc3	2.46	0.06	0.69	0.33	3.14	1.79	0.98	7.49	0.7	5.94	3.78	11.28	3.71	1.04
pca.cr.fc.v4.tnh.nc4	2.47	0.06	0.69	0.33	3.05	1.74	0.98	3.56	0.22	3.32	3.05	6.61	0.51	1.04
pca.cr.fc.v4.tnh.nc5	2.47	0.06	0.69	0.34	3.14	1.79	0.98	3.56	0.22	3.32	3.05	6.61	0.51	1.04
pca.cr.fc.v4.exp.nc2	2.47	0.06	0.69	0.39	3.1	1.68	0.98	18.34	3.8	13.78	6.61	24.95	11.72	1.18
pca.cr.fc.v4.exp.nc3	2.46	0.06	0.69	0.38	3.19	1.72	0.98	9.67	1.11	7.44	4.16	13.83	5.5	1.1
pca.cr.fc.v4.exp.nc4	2.46	0.06	0.69	0.38	3.19	1.72	0.98	13.86	1.92	9.8	0.38	14.24	13.48	1.14
pca.cr.fc.v4.exp.nc5	2.46	0.06	0.69	0.38	3.19	1.72	0.98	12.42	1.55	8.82	1.06	13.48	11.36	1.01
pca.cr.fc.v5.pol.nc2	0.11	0	0.04	0.09	0.28	0	1	16.59	2.79	11.81	1.96	18.55	14.62	1.17
pca.cr.fc.v5.pol.nc3	0.07	0	0.03	0.06	0.21	0	1	8.17	1.14	7.55	6.87	15.05	1.3	1.08
pca.cr.fc.v5.pol.nc4	0.06	0	0.02	0.03	0.11	0.01	1	13.43	1.82	9.54	1.3	14.73	12.12	1.13
pca.cr.fc.v5.pol.nc5	0.05	0	0.02	0.03	0.11	0	1	7.01	0.75	6.13	5.12	12.12	1.89	1.07
pca.cr.fc.v5.sin.nc2	0.08	0	0.03	0.08	0.23	0	1	11.43	1.9	9.74	7.58	19.12	3.75	1.11
pca.cr.fc.v5.sin.nc3	0.09	0	0.03	0.06	0.22	0.01	1	7.5	1.03	7.19	6.88	14.37	0.62	1.07
pca.cr.fc.v5.sin.nc4	0.07	0	0.02	0.03	0.12	0.02	1	6.55	0.56	5.27	3.56	10.11	2.99	1.07
pca.cr.fc.v5.sin.nc5	0.07	0	0.02	0.03	0.12	0.02	1	6.55	0.56	5.27	3.56	10.11	2.99	1.07
pca.cr.fc.v5.tnh.nc2	0.08	0	0.03	0.07	0.23	0	1	9.76	1.88	9.69	9.62	19.39	0.14	1.1
pca.cr.fc.v5.tnh.nc3	0.1	0	0.03	0.06	0.22	0.01	1	7.56	0.97	6.98	6.34	13.9	1.22	1.06
pca.cr.fc.v5.tnh.nc4	0.08	0	0.02	0.03	0.13	0.02	1	6.13	0.47	4.83	3.01	9.14	3.12	1.06
pca.cr.fc.v5.tnh.nc5	0.08	0	0.02	0.03	0.13	0.03	1	6.13	0.47	4.83	3.01	9.14	3.12	1.06
pca.cr.fc.v5.exp.nc2	0.03	0	0.01	0.03	0.09	0	1	20.94	4.86	15.58	6.85	27.8	14.09	1.21
pca.cr.fc.v5.exp.nc3	0.02	0	0.01	0.02	0.06	0	1	12.23	1.67	9.15	4.23	16.45	8	1.12
pca.cr.fc.v5.exp.nc4	0.02	0	0.01	0.01	0.04	0	1	16.43	2.7	11.62	0.42	16.85	16.01	1.16
pca.cr.fc.v5.exp.nc5	0.02	0	0.01	0.01	0.04	0	1	12.5	1.69	9.18	3.5	16.01	9	1.04
pca.cr.km.v1.pol.nc2	2.18	0.07	0.76	1.65	5.68	0.39	1.02	96.05	144.39	84.97	72.21	168.25	23.84	1.08
pca.cr.km.v1.pol.nc3	1.76	0.04	0.56	1.02	4.13	0.54	1.02	22.32	5.06	15.9	2.73	25.06	19.59	1.22

Table D: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.cr.km.v1.pol.nc4	1.63	0.03	0.5	0.74	2.91	0.1	1.02	4.46	0.32	4.01	3.51	7.97	0.94	1.04
pca.cr.km.v1.pol.nc5	1.62	0.03	0.49	0.73	2.91	0.1	1.02	5.28	0.35	4.19	2.69	7.97	2.59	1.05
pca.cr.km.v1.sin.nc2	2.1	0.07	0.75	1.69	5.49	0.14	1.02	88.24	111.59	74.7	58.07	146.31	30.17	1.88
pca.cr.km.v1.sin.nc3	1.79	0.04	0.59	1.13	4.21	0.57	1.02	25.54	6.58	18.14	2.49	28.03	23.04	1.26
pca.cr.km.v1.sin.nc4	1.66	0.03	0.52	0.86	3.02	0.01	1.02	8.01	0.9	6.7	5.06	13.08	2.95	1.05
pca.cr.km.v1.sin.nc5	1.64	0.03	0.51	0.82	3.02	0.01	1.02	6.88	0.86	6.55	6.19	13.08	0.69	1.07
pca.cr.km.v1.tnh.nc2	2.08	0.07	0.76	1.76	5.45	0.04	1.02	81.68	90.99	67.45	49.27	130.95	32.41	1.82
pca.cr.km.v1.tnh.nc3	1.81	0.05	0.6	1.21	4.22	0.45	1.02	26.44	7.24	19.02	4.96	31.4	21.48	1.26
pca.cr.km.v1.tnh.nc4	1.69	0.04	0.54	0.94	3.1	0.11	1.02	9.63	1.19	7.71	5.12	14.74	4.51	1.05
pca.cr.km.v1.tnh.nc5	1.67	0.04	0.52	0.86	3.1	0.11	1.02	7.38	1.09	7.37	7.36	14.74	0.01	1.07
pca.cr.km.v1.exp.nc2	1.61	0.03	0.46	0.41	2.23	1.02	1.02	47.97	27.66	37.19	21.54	69.52	26.43	1.48
pca.cr.km.v1.exp.nc3	1.6	0.03	0.45	0.3	1.96	1.11	1.02	19.44	3.8	13.78	1.34	20.78	18.1	1.19
pca.cr.km.v1.exp.nc4	1.59	0.03	0.45	0.3	2.2	1.02	1.02	6.1	0.4	4.46	1.61	7.72	4.49	1.06
pca.cr.km.v1.exp.nc5	1.59	0.03	0.45	0.3	2.2	1.02	1.02	21.75	7.33	19.14	16.12	37.87	5.63	1.22
pca.cr.km.v2.pol.nc2	3.22	0.14	1.05	1.96	7.01	0.27	1.03	102.96	165.19	90.88	76.92	179.88	26.04	2.03
pca.cr.km.v2.pol.nc3	3.06	0.11	0.9	1.12	5.43	0.9	1.03	25.09	6.39	17.88	3.17	28.26	21.92	1.25
pca.cr.km.v2.pol.nc4	3.02	0.1	0.86	0.72	4.25	1.53	1.03	5.03	0.49	4.94	4.86	9.88	0.17	1.05
pca.cr.km.v2.pol.nc5	3.01	0.1	0.86	0.71	4.25	1.53	1.03	6.69	0.55	5.24	3.19	9.88	3.5	1.07
pca.cr.km.v2.sin.nc2	3.18	0.14	1.04	1.98	6.83	0.28	1.03	94.61	128.26	80.08	62.26	156.86	32.35	1.95
pca.cr.km.v2.sin.nc3	3.08	0.11	0.92	1.22	5.51	0.88	1.03	28.53	8.19	20.24	2.29	30.81	26.24	1.29
pca.cr.km.v2.sin.nc4	3.04	0.1	0.87	0.84	4.36	1.42	1.03	8.79	1.2	7.74	6.53	15.31	2.26	1.07
pca.cr.km.v2.sin.nc5	3.02	0.1	0.87	0.8	4.36	1.42	1.03	8.43	1.18	7.69	6.89	15.31	1.54	1.08
pca.cr.km.v2.tnh.nc2	3.18	0.14	1.05	2.01	6.76	0.57	1.03	87.6	104.87	72.41	53.05	140.65	34.55	1.88
pca.cr.km.v2.tnh.nc3	3.1	0.11	0.93	1.3	5.53	0.84	1.03	29.5	8.94	21.15	4.88	34.38	24.63	1.3
pca.cr.km.v2.tnh.nc4	3.05	0.1	0.89	0.94	4.43	1.32	1.03	10.48	1.53	8.76	6.6	17.08	3.88	1.07
pca.cr.km.v2.tnh.nc5	3.03	0.1	0.88	0.87	4.43	1.32	1.03	8.96	1.46	8.55	8.12	17.08	0.84	1.09
pca.cr.km.v2.exp.nc2	3	0.09	0.84	0.42	3.62	2.39	1.03	53.99	35.07	41.88	24.35	78.33	29.64	1.54
pca.cr.km.v2.exp.nc3	2.98	0.09	0.83	0.31	3.35	2.48	1.03	21.87	4.82	15.53	2	23.88	19.87	1.22
pca.cr.km.v2.exp.nc4	2.98	0.09	0.83	0.31	3.61	2.39	1.03	6.63	0.48	4.88	1.94	8.57	4.68	1.07
pca.cr.km.v2.exp.nc5	2.97	0.09	0.83	0.31	3.61	2.39	1.03	24.25	8.79	20.96	17.05	41.3	7.2	1.24
pca.cr.km.v3.pol.nc2	2.39	0.06	0.67	0.24	2.73	1.84	0.98	19.79	3.93	14.03	1.31	21.1	18.48	1.2
pca.cr.km.v3.pol.nc3	2.4	0.06	0.67	0.09	2.61	2.24	0.98	6.71	0.76	6.17	5.58	12.29	1.13	1.08
pca.cr.km.v3.pol.nc4	2.4	0.06	0.67	0.09	2.6	2.24	0.98	0.77	0.01	0.61	0.39	1.16	0.38	1.01
pca.cr.km.v3.pol.nc5	2.4	0.06	0.67	0.05	2.5	2.3	0.98	4.91	0.45	4.72	4.53	9.43	0.38	1.05

Table D: continued

cr = cluster wise regression, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.cr.km.v3.sin.nc2	2.39	0.06	0.67	0.37	2.86	1.51	0.98	20.29	4.12	14.35	0.24	20.53	20.04	1.2
pca.cr.km.v3.sin.nc3	2.39	0.06	0.66	0.1	2.62	2.21	0.98	7.32	0.72	6.01	4.31	11.63	3.01	1.04
pca.cr.km v3.sin.nc4	2.4	0.06	0.67	0.11	2.62	2.19	0.98	0.35	0	0.27	0.17	0.52	0.18	1
pca.cr.km.v3.sin.nc5	2.4	0.06	0.67	0.06	2.5	2.29	0.98	3.99	0.28	3.74	3.47	7.46	0.52	1.04
pca.cr.km.v3.tnh.nc2	2.38	0.06	0.67	0.42	2.91	1.39	0.98	19.53	3.83	13.84	1.29	20.82	18.23	1.2
pca.cr.km.v3.tnh.nc3	2.39	0.06	0.66	0.11	2.62	2.19	0.98	7.38	0.69	5.87	3.79	11.17	3.58	1.04
pca.cr.km.v3.tnh.nc4	2.4	0.06	0.67	0.13	2.62	2.16	0.98	0.33	0	0.32	0.31	0.65	0.02	1
pca.cr.km.v3.tnh.nc5	2.4	0.06	0.67	0.07	2.52	2.27	0.98	3.58	0.21	3.28	2.94	6.52	0.65	1.04
pca.cr.km.v3.exp.nc2	2.4	0.06	0.66	0.04	2.48	2.32	0.98	18.04	3.7	13.61	6.69	24.73	11.35	1.18
pca.cr.km.v3.exp.nc3	2.4	0.06	0.66	0.03	2.46	2.35	0.98	9.53	1.08	7.35	4.13	13.66	5.41	1.1
pca.cr.km.v3.exp.nc4	2.4	0.06	0.66	0.03	2.46	2.35	0.98	4.54	0.24	3.45	1.78	6.31	2.76	1.05
pca.cr.km.v3.exp.nc5	2.4	0.06	0.66	0.02	2.43	2.37	0.98	12.85	3.09	12.42	11.99	24.83	0.86	1.13
pca.cr.km.v4.pol.nc2	2.47	0.06	0.69	0.39	3.07	1.71	0.98	20.13	4.06	14.26	1.1	21.23	19.03	1.2
pca.cr.km.v4.pol.nc3	2.46	0.06	0.69	0.35	3.16	1.76	0.98	6.81	0.78	6.24	5.62	12.42	1.19	1.06
pca.cr.km.v4.pol.nc4	2.46	0.06	0.69	0.33	3.07	1.71	0.98	0.75	0.01	0.65	0.51	1.27	0.24	1.01
pca.cr.km.v4.pol.nc5	2.46	0.06	0.69	0.32	3.07	1.71	0.98	4.92	0.46	4.8	4.68	9.6	0.24	1.05
pca.cr.km.v4.sin.nc2	2.46	0.06	0.69	0.45	3.23	1.73	0.98	20.64	4.26	14.59	0.01	20.64	20.63	1.21
pca.cr.km.v4.sin.nc3	2.46	0.06	0.69	0.34	3.15	1.78	0.98	7.43	0.74	6.08	4.32	11.75	3.12	1.04
pca.cr.km.v4.sin.nc4	2.46	0.06	0.69	0.32	3.06	1.73	0.98	0.32	0	0.23	0.05	0.38	0.27	1
pca.cr.km.v4.sin.nc5	2.46	0.06	0.69	0.31	3.06	1.73	0.98	3.98	0.29	3.79	3.6	7.58	0.38	1.04
pca.cr.km.v4.tnh.nc2	2.46	0.06	0.69	0.47	3.3	1.72	0.98	19.86	3.95	14.06	1.08	20.94	18.77	1.2
pca.cr.km.v4.tnh.nc3	2.46	0.06	0.69	0.33	3.14	1.79	0.98	7.49	0.7	5.94	3.78	11.28	3.71	1.04
pca.cr.km.v4.tnh.nc4	2.46	0.06	0.69	0.31	3.05	1.74	0.98	0.29	0	0.26	0.22	0.51	0.06	1
pca.cr.km.v4.tnh.nc5	2.46	0.06	0.69	0.3	3.05	1.74	0.98	3.56	0.22	3.32	3.05	6.61	0.51	1.04
pca.cr.km.v4.exp.nc2	2.47	0.06	0.69	0.39	3.1	1.68	0.98	18.34	3.8	13.78	6.61	24.95	11.72	1.18
pca.cr.km.v4.exp.nc3	2.46	0.06	0.69	0.38	3.19	1.72	0.98	9.67	1.11	7.44	4.16	13.83	5.5	1.1
pca.cr.km.v4.exp.nc4	2.46	0.06	0.69	0.36	3.1	1.68	0.98	4.62	0.24	3.48	1.7	6.32	2.92	1.05
pca.cr.km.v4.exp.nc5	2.46	0.06	0.69	0.35	3.1	1.68	0.98	12.82	3.04	12.32	11.8	24.63	1.02	1.13
pca.cr.km.v5.pol.nc2	0.17	0	0.07	0.17	0.57	0.01	1	22.74	5.19	16.11	1.34	24.08	21.39	1.23
pca.cr.km.v5.pol.nc3	0.07	0	0.03	0.06	0.21	0	1	8.17	1.14	7.55	6.87	15.05	1.3	1.08
pca.cr.km.v5.pol.nc4	0.08	0	0.03	0.06	0.21	0.02	1	3.25	0.11	2.31	0.4	3.64	2.85	1.03
pca.cr.km.v5.pol.nc5	0.05	0	0.02	0.03	0.11	0	1	7.49	0.78	6.23	4.64	12.12	2.85	1.07
pca.cr.km.v5.sin.nc2	0.27	0	0.11	0.26	0.91	0.02	1	23.24	5.4	16.44	0.25	23.49	22.99	1.23
pca.cr.km.v5.sin.nc3	0.09	0	0.03	0.06	0.22	0.01	1	7.5	1.03	7.19	6.88	14.37	0.62	1.07

Table D: continued

cr = cluster wise regression, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.cr.km.v5.sin.nc4	0.1	0	0.03	0.07	0.22	0.02	1	2.82	0.08	2	0.17	2.99	2.64	1.03
pca.cr.km.v5.sin.nc5	0.06	0	0.02	0.04	0.12	0	1	6.55	0.56	5.27	3.56	10.11	2.99	1.07
pca.cr.km.v5.tnh.nc2	0.31	0	0.12	0.3	1.04	0.02	1	22.46	5.06	15.91	1.32	23.79	21.14	1.22
pca.cr.km.v5.tnh.nc3	0.1	0	0.03	0.06	0.22	0.01	1	7.56	0.97	6.98	6.34	13.9	1.22	1.06
pca.cr.km.v5.tnh.nc4	0.11	0	0.04	0.07	0.24	0.02	1	2.78	0.08	1.98	0.34	3.12	2.44	1.03
pca.cr.km.v5.tnh.nc5	0.06	0	0.02	0.04	0.13	0.01	1	6.13	0.47	4.83	3.01	9.14	3.12	1.06
pca.cr.km.v5.exp.nc2	0.03	0	0.01	0.03	0.09	0	1	20.94	4.86	15.58	6.85	27.8	14.09	1.21
pca.cr.km.v5.exp.nc3	0.02	0	0.01	0.02	0.06	0	1	12.23	1.67	9.15	4.23	16.45	8	1.12
pca.cr.km.v5.exp.nc4	0.02	0	0.01	0.02	0.06	0	1	7.11	0.54	5.19	1.82	8.93	5.29	1.07
pca.cr.km.v5.exp.nc5	0.01	0	0	0.01	0.04	0	1	15.62	3.95	14.05	12.28	27.9	3.34	1.16
pca.cr.kh.v1.pol.nc2	3.01	0.13	1.01	2.04	6.67	0.5	1.02	46.33	25.8	35.92	20.83	67.15	25.5	1.46
pca.cr.kh.v1.pol.nc3	3.37	0.16	1.12	2.23	7.87	0.67	1.02	37.09	19.14	30.93	23.19	60.28	13.9	1.23
pca.cr.kh.v1.pol.nc4	2.17	0.09	0.82	2.01	6.69	0.2	1.02	14.37	2.84	11.92	8.8	23.17	5.56	1.14
pca.cr.kh.v1.pol.nc5	1.58	0.03	0.47	0.59	2.55	0.8	1.02	10.39	1.98	9.95	9.48	19.87	0.91	1.1
pca.cr.kh.v1.sin.nc2	2.79	0.11	0.92	1.78	6.23	0.47	1.02	39.87	19.48	31.21	18.92	58.79	20.95	1.4
pca.cr.kh.v1.sin.nc3	3.06	0.13	1	1.87	6.28	0.6	1.02	31.8	14	26.46	19.72	51.52	12.08	1.2
pca.cr.kh.v1.sin.nc4	2.17	0.09	0.81	1.97	6.31	0.07	1.02	11.49	1.56	8.84	4.94	16.43	6.55	1.11
pca.cr.kh.v1.sin.nc5	1.78	0.04	0.56	0.92	3.77	0.62	1.02	13.83	3.64	13.5	13.18	26.98	0.67	1.14
pca.cr.kh.v1.tnh.nc2	2.63	0.1	0.86	1.66	5.98	0.44	1.02	36.03	16.18	28.44	17.88	53.91	18.15	1.36
pca.cr.kh.v1.tnh.nc3	2.85	0.11	0.92	1.7	5.82	0.56	1.02	29.53	12.11	24.61	18.42	47.95	11.11	1.18
pca.cr.kh.v1.tnh.nc4	1.55	0.03	0.46	0.61	2.75	0.63	1.02	10.05	1.62	8.99	7.78	17.83	2.26	1.08
pca.cr.kh.v1.tnh.nc5	1.76	0.04	0.55	0.91	3.67	0.64	1.02	13.48	3.49	13.21	12.94	26.42	0.53	1.13
pca.cr.kh.v1.exp.nc2	1.69	0.04	0.53	0.9	3.14	0.02	1.02	23	5.95	17.25	8.13	31.13	14.87	1.23
pca.cr.kh.v1.exp.nc3	1.65	0.03	0.5	0.73	2.73	0.58	1.02	9.88	1.56	8.82	7.61	17.49	2.26	1.1
pca.cr.kh.v1.exp.nc4	1.67	0.04	0.56	1.11	3.85	0.02	1.02	10.32	1.59	8.92	7.24	17.56	3.08	1.1
pca.cr.kh.v1.exp.nc5	1.61	0.03	0.48	0.63	3.38	0.84	1.02	5.98	0.44	4.7	2.9	8.87	3.08	1.06
pca.cr.kh.v2.pol.nc2	3.88	0.2	1.25	2.33	7.85	0.45	1.03	50.22	30.42	39	22.8	73.02	27.41	1.5
pca.cr.kh.v2.pol.nc3	4.3	0.24	1.35	2.26	9.21	1.99	1.03	39.54	22.33	33.41	25.88	65.42	13.66	1.26
pca.cr.kh.v2.pol.nc4	3.19	0.15	1.09	2.28	7.96	0.03	1.03	16.2	3.54	13.31	9.58	25.78	6.62	1.16
pca.cr.kh.v2.pol.nc5	2.96	0.09	0.84	0.57	3.89	2.22	1.03	11.89	2.39	10.93	9.88	21.78	2.01	1.12
pca.cr.kh.v2.sin.nc2	3.66	0.18	1.18	2.15	7.4	0.03	1.03	43.29	23.03	33.93	20.71	64	22.58	1.43
pca.cr.kh.v2.sin.nc3	4	0.2	1.24	2.01	7.63	1.26	1.03	33.91	16.38	28.62	22.08	56	11.83	1.22
pca.cr.kh.v2.sin.nc4	3.2	0.15	1.08	2.24	7.58	0.31	1.03	13.22	2.04	10.11	5.43	18.65	7.79	1.13
pca.cr.kh.v2.sin.nc5	3.01	0.1	0.89	1.13	5.1	0.47	1.03	15.38	4.22	14.53	13.63	29.02	1.75	1.15

Table D: continued

cr = cluster wise regression, km=k-means clustering, kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.cr.kh.v2.tnh.nc2	3.57	0.17	1.13	2	7.15	0.36	1.03	39.19	19.2	30.98	19.6	58.78	19.59	1.39
pca.cr.kh.v2.tnh.nc3	3.79	0.18	1.18	1.94	7.16	0.57	1.03	31.53	14.21	26.66	20.67	52.2	10.86	1.21
pca.cr.kh.v2.tnh.nc4	2.93	0.09	0.83	0.53	4.09	2.06	1.03	10.56	1.94	9.86	9.1	19.66	1.46	1.09
pca.cr.kh.v2.tnh.nc5	3.01	0.1	0.89	1.09	5	0.61	1.03	15.01	4.06	14.24	13.42	28.43	1.59	1.15
pca.cr.kh.v2.exp.nc2	3.08	0.1	0.89	0.93	4.56	1.35	1.03	24.64	6.72	18.33	8.03	32.67	16.62	1.25
pca.cr.kh.v2.exp.nc3	3.04	0.1	0.87	0.74	4.11	1.95	1.03	11.21	1.9	9.76	8.05	19.26	3.16	1.11
pca.cr.kh.v2.exp.nc4	3.05	0.11	0.9	1.14	5.31	1.36	1.03	11.9	2	10	7.63	19.53	4.27	1.12
pca.cr.kh.v2.exp.nc5	3	0.09	0.85	0.64	4.78	2.19	1.03	7.51	0.67	5.78	3.24	10.75	4.27	1.08
pca.cr.kh.v3.pol.nc2	2.38	0.06	0.66	0.19	2.67	1.97	0.98	17.27	3.34	12.92	5.96	23.23	11.31	1.17
pca.cr.kh.v3.pol.nc3	2.38	0.06	0.66	0.23	2.75	1.87	0.98	10.11	1.93	9.81	9.51	19.62	0.59	1.1
pca.cr.kh.v3.pol.nc4	2.39	0.06	0.66	0.21	2.66	1.97	0.98	2.85	0.12	2.46	1.99	4.84	0.86	1.03
pca.cr.kh.v3.pol.nc5	2.41	0.06	0.67	0.04	2.47	2.34	0.98	5.21	0.46	4.82	4.4	9.61	0.81	1.04
pca.cr.kh.v3.sin.nc2	2.38	0.06	0.66	0.21	2.67	1.99	0.98	16.26	2.85	11.94	4.56	20.81	11.7	1.16
pca.cr.kh.v3.sin.nc3	2.38	0.06	0.66	0.25	2.75	1.81	0.98	8.97	1.47	8.57	8.15	17.12	0.82	1.09
pca.cr.kh.v3.sin.nc4	2.39	0.06	0.66	0.22	2.65	1.93	0.98	2.04	0.05	1.6	1	3.04	1.03	1.02
pca.cr.kh.v3.sin.nc5	2.41	0.06	0.67	0.11	2.69	2.19	0.98	7.09	0.88	6.64	6.16	13.25	0.94	1.06
pca.cr.kh.v3.tnh.nc2	2.38	0.06	0.66	0.23	2.66	1.88	0.98	15.58	2.58	11.35	3.84	19.42	11.74	1.16
pca.cr.kh.v3.tnh.nc3	2.38	0.06	0.66	0.26	2.75	1.8	0.98	8.37	1.16	7.63	6.81	15.18	1.56	1.08
pca.cr.kh.v3.tnh.nc4	2.41	0.06	0.67	0.04	2.49	2.32	0.98	5.05	0.43	4.62	4.14	9.19	0.91	1.04
pca.cr.kh.v3.tnh.nc5	2.41	0.06	0.67	0.12	2.71	2.16	0.98	7.08	0.88	6.64	6.16	13.24	0.92	1.06
pca.cr.kh.v3.exp.nc2	2.32	0.06	0.67	0.64	3.35	0.94	0.98	19.22	4.46	14.94	8.78	28	10.44	1.19
pca.cr.kh.v3.exp.nc3	2.36	0.06	0.67	0.46	3.27	1.48	0.98	6.83	0.84	6.49	6.13	12.96	0.7	1.07
pca.cr.kh.v3.exp.nc4	2.33	0.06	0.69	0.87	3.67	0.62	0.98	5.76	0.61	5.54	5.32	11.08	0.43	1.06
pca.cr.kh.v3.exp.nc5	2.38	0.06	0.67	0.32	2.89	1.45	0.98	1.39	0.03	1.2	0.96	2.35	0.43	1.01
pca.cr.kh.v4.pol.nc2	2.46	0.06	0.69	0.31	3.03	1.92	0.98	17.59	3.45	13.13	5.98	23.57	11.6	1.18
pca.cr.kh.v4.pol.nc3	2.45	0.06	0.68	0.29	3.03	2.05	0.98	10.54	2.03	10.07	9.58	20.12	0.96	1.1
pca.cr.kh.v4.pol.nc4	2.45	0.06	0.68	0.31	3.21	1.98	0.98	2.95	0.13	2.55	2.06	5.01	0.89	1.03
pca.cr.kh.v4.pol.nc5	2.44	0.06	0.68	0.26	3.17	1.98	0.98	5.25	0.46	4.81	4.33	9.58	0.92	1.04
pca.cr.kh.v4.sin.nc2	2.45	0.06	0.69	0.31	3.04	1.93	0.98	16.55	2.94	12.13	4.54	21.09	12.01	1.17
pca.cr.kh.v4.sin.nc3	2.45	0.06	0.68	0.28	2.91	2.06	0.98	9.02	1.54	8.78	8.54	17.56	0.49	1.09
pca.cr.kh.v4.sin.nc4	2.45	0.06	0.68	0.3	3.2	1.99	0.98	2.12	0.06	1.67	1.04	3.16	1.07	1.02
pca.cr.kh.v4.sin.nc5	2.45	0.06	0.68	0.29	3.17	1.98	0.98	7.17	0.89	6.67	6.12	13.3	1.05	1.06
pca.cr.kh.v4.tnh.nc2	2.45	0.06	0.69	0.31	3.05	1.92	0.98	15.85	2.66	11.53	3.81	19.66	12.04	1.16
pca.cr.kh.v4.tnh.nc3	2.45	0.06	0.68	0.27	2.82	2.06	0.98	8.41	1.22	7.81	7.16	15.57	1.24	1.08

Table D: continued

cr = cluster wise regression, kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.cr.kh.v4.tnh.nc4	2.42	0.06	0.67	0.11	2.69	2.31	0.98	5.08	0.42	4.61	4.08	9.16	1	1.04
pca.cr.kh.v4.tnh.nc5	2.45	0.06	0.68	0.29	3.16	1.98	0.98	7.16	0.89	6.66	6.12	13.29	1.04	1.06
pca.cr.kh.v4.exp.nc2	2.4	0.06	0.68	0.48	3.04	1.13	0.98	19.58	4.62	15.2	8.87	28.45	10.71	1.2
pca.cr.kh.v4.exp.nc3	2.43	0.06	0.68	0.41	3.01	1.71	0.98	6.93	0.9	6.72	6.51	13.44	0.41	1.07
pca.cr.kh.v4.exp.nc4	2.38	0.06	0.69	0.7	3.61	1.16	0.98	5.85	0.63	5.63	5.4	11.25	0.46	1.06
pca.cr.kh.v4.exp.nc5	2.42	0.06	0.67	0.2	2.91	2.06	0.98	1.35	0.03	1.14	0.89	2.24	0.46	1.01
pca.cr.kh.v5.pol.nc2	0.16	0	0.05	0.11	0.43	0.03	1	20.15	4.43	14.89	6.11	26.26	14.04	1.2
pca.cr.kh.v5.pol.nc3	0.16	0	0.07	0.18	0.55	0.01	1	12.2	2.56	11.32	10.35	22.56	1.85	1.12
pca.cr.kh.v5.pol.nc4	0.16	0	0.06	0.14	0.44	0.01	1	5.38	0.33	4.07	2.04	7.42	3.34	1.05
pca.cr.kh.v5.pol.nc5	0.04	0	0.01	0.02	0.07	0	1	6.96	0.77	6.2	5.34	12.3	1.63	1.07
pca.cr.kh.v5.sin.nc2	0.18	0	0.06	0.12	0.41	0.05	1	19.12	3.87	13.91	4.67	23.78	14.45	1.19
pca.cr.kh.v5.sin.nc3	0.17	0	0.07	0.19	0.6	0.02	1	11.64	2.05	10.13	8.35	19.99	3.29	1.12
pca.cr.kh.v5.sin.nc4	0.17	0	0.06	0.14	0.48	0.01	1	4.54	0.22	3.29	1.03	5.57	3.52	1.05
pca.cr.kh.v5.sin.nc5	0.07	0	0.03	0.09	0.3	0.01	1	8.76	1.3	8.05	7.27	16.03	1.5	1.09
pca.cr.kh.v5.tnh.nc2	0.2	0	0.07	0.13	0.53	0.05	1	18.42	3.55	13.32	3.94	22.36	14.48	1.18
pca.cr.kh.v5.tnh.nc3	0.18	0	0.07	0.19	0.61	0.02	1	11.03	1.7	9.23	6.98	18.01	4.05	1.11
pca.cr.kh.v5.tnh.nc4	0.04	0	0.01	0.03	0.09	0	1	6.7	0.72	5.99	5.17	11.87	1.53	1.07
pca.cr.kh.v5.tnh.nc5	0.08	0	0.03	0.1	0.32	0.01	1	8.77	1.29	8.05	7.25	16.02	1.51	1.09
pca.cr.kh.v5.exp.nc2	0.54	0	0.18	0.39	1.5	0.05	1	22.15	5.71	16.9	9	31.14	13.15	1.22
pca.cr.kh.v5.exp.nc3	0.34	0	0.13	0.33	0.94	0.03	1	9.45	1.29	8.02	6.28	15.73	3.17	1.09
pca.cr.kh.v5.exp.nc4	0.65	0.01	0.25	0.62	1.82	0.04	1	8.36	1	7.06	5.45	13.81	2.9	1.08
pca.cr.kh.v5.exp.nc5	0.21	0	0.09	0.26	0.97	0.03	1	3.88	0.16	2.83	0.98	4.87	2.9	1.04
pca.cr.at.v1.pol.nc5	1.6	0.03	0.48	0.67	2.77	0.89	1.02	5.48	0.38	4.38	2.89	8.37	2.59	0.97
pca.cr.at.v1.sin.nc5	1.63	0.03	0.51	0.88	3.27	0.18	1.02	3.26	0.17	2.93	2.56	5.82	0.69	1.03
pca.cr.at.v1.tnh.nc5	1.7	0.05	0.59	1.29	4.01	0.02	1.02	18.24	4.31	14.67	9.9	28.14	8.34	1.18
pca.cr.at.v1.exp.nc5	1.54	0.02	0.43	0	1.54	1.53	1.02	56.28	50.79	50.39	43.72	100	12.57	0.56
pca.cr.at.v2.pol.nc5	2.98	0.09	0.85	0.65	4.12	2.29	1.03	5.3	0.31	3.96	1.8	7.1	3.5	0.98
pca.cr.at.v2.sin.nc5	3.01	0.1	0.87	0.85	4.6	1.6	1.03	4.41	0.28	3.72	2.87	7.28	1.54	1.04
pca.cr.at.v2.tnh.nc5	3.07	0.11	0.92	1.26	5.35	1.41	1.03	20.76	5.48	16.55	10.8	31.56	9.96	1.21
pca.cr.at.v2.exp.nc5	2.92	0.09	0.81	0	2.92	2.92	1.03	57.39	51.09	50.54	42.61	100	14.79	0.57
pca.cr.at.v3.pol.nc5	2.4	0.06	0.67	0.06	2.5	2.3	0.98	12.55	1.67	9.15	3.12	15.67	9.43	0.97
pca.cr.at.v3.sin.nc5	2.4	0.06	0.67	0.06	2.5	2.29	0.98	3.99	0.28	3.74	3.48	7.46	0.51	1.04
pca.cr.at.v3.tnh.nc5	2.4	0.06	0.67	0.12	2.61	2.14	0.98	1.17	0.02	0.88	0.4	1.57	0.78	1.01
pca.cr.at.v3.exp.nc5	2.4	0.06	0.67	0	2.4	2.4	0.98	52.54	50.13	50.06	47.46	100	5.09	0.53

Table D: continued

cr = cluster wise regression,kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters, pca= data prepared using mean with PCA, mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modeling	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.oclstr.fc.nc1.e1	1.49	0.04	0.55	1.3	4.98	0.01	1	54.55	44.67	47.26	38.62	93.17	15.93	1.55
pca.oclstr.fc.nc1.e2	5.29	0.44	1.85	4.04	15.75	0.38	1	26.69	13.56	26.04	25.37	52.06	1.32	1.27
pca.oclstr.fc.nc1.e3	6.26	0.6	2.15	4.56	12.51	0.44	1.01	20.61	6.67	18.26	15.57	36.18	5.04	1.21
pca.oclstr.fc.nc1.e4	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.fc.nc1.e5	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.fc.nc2.e1	0.94	0.01	0.31	0.63	2.24	0.19	1	72.18	90.17	67.15	61.71	133.88	10.47	1.72
pca.oclstr.fc.nc2.e2	4.8	0.39	1.73	3.96	15.98	0.44	1	37.62	27.6	37.15	36.68	74.3	0.94	1.38
pca.oclstr.fc.nc2.e3	4.8	0.39	1.73	3.96	15.98	0.44	1	37.62	27.6	37.15	36.68	74.3	0.94	1.38
pca.oclstr.fc.nc2.e4	11.25	1.93	3.85	8.12	25.33	0.96	1.02	4.29	0.19	3.07	0.67	4.96	3.63	1.04
pca.oclstr.fc.nc2.e5	11.25	1.93	3.85	8.12	25.33	0.96	1.02	4.29	0.19	3.07	0.67	4.96	3.63	1.04
pca.oclstr.fc.nc3.e1	0.85	0.01	0.3	0.64	2.08	0.07	1	7.9	0.63	5.63	1.03	8.93	6.87	0.99
pca.oclstr.fc.nc3.e2	3.36	0.25	1.38	3.66	12.7	0	1	8.29	0.7	5.9	0.91	9.2	7.38	1.01
pca.oclstr.fc.nc3.e3	6.43	0.68	2.3	5.2	16.46	0.43	1.01	6.55	0.48	4.91	2.31	8.86	4.25	1.02
pca.oclstr.fc.nc3.e4	11.38	1.68	3.6	6.25	22.57	0.61	1.01	8.47	1.34	8.18	7.88	16.35	0.59	0.92
pca.oclstr.fc.nc3.e5	11.38	1.68	3.6	6.25	22.57	0.61	1.01	8.47	1.34	8.18	7.88	16.35	0.59	0.92
pca.oclstr.fc.nc4.e1	1.3	0.03	0.47	1.07	4.17	0.13	1	60.3	68.29	58.43	56.51	116.8	3.79	1.6
pca.oclstr.fc.nc4.e2	2.8	0.13	1	2.25	8.1	0.17	1	1.75	0.06	1.67	1.58	3.33	0.17	1.02
pca.oclstr.fc.nc4.e3	5.59	0.55	2.05	4.85	16.49	1.1	1	1.65	0.05	1.55	1.45	3.1	0.21	0.98
pca.oclstr.fc.nc4.e4	7.68	0.93	2.67	5.81	20.81	1.1	1.01	2.84	0.14	2.69	2.52	5.36	0.32	1.03
pca.oclstr.fc.nc4.e5	7.68	0.93	2.67	5.81	20.81	1.1	1.01	2.84	0.14	2.69	2.52	5.36	0.32	1.03
pca.oclstr.fc.nc5.e1	0.25	0	0.13	0.39	1.3	0	1	41.45	28.52	37.76	33.67	75.12	7.78	1.41
pca.oclstr.fc.nc5.e2	3.4	0.17	1.15	2.35	9.36	0	1	118.72	165.61	91	49.67	168.39	69.05	0.5
pca.oclstr.fc.nc5.e3	4.66	0.42	1.81	4.54	17.51	0	1	132.46	213.31	103.28	61.53	193.99	70.93	0.38
pca.oclstr.fc.nc5.e4	7.21	1	2.78	6.94	26.2	0	1.01	88.78	80.08	63.28	11.22	100	77.57	0.89
pca.oclstr.fc.nc5.e5	10.75	1.67	3.59	7.2	27.05	0	1.02	92.85	86.72	65.85	7.15	100	85.7	0.93
pca.oclstr.km.nc1.e1	1.49	0.04	0.55	1.3	4.98	0.01	1	54.55	44.67	47.26	38.62	93.17	15.93	1.55
pca.oclstr.km.nc1.e2	5.29	0.44	1.85	4.04	15.75	0.38	1	26.69	13.56	26.04	25.37	52.06	1.32	1.27
pca.oclstr.km.nc1.e3	6.26	0.6	2.15	4.56	12.51	0.44	1.01	20.61	6.67	18.26	15.57	36.18	5.04	1.21
pca.oclstr.km.nc1.e4	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.km.nc1.e5	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.km.nc2.e1	0.24	0	0.08	0.16	0.59	0.05	1	51.95	32.46	40.29	23.39	75.35	28.56	1.52
pca.oclstr.km.nc2.e2	1.48	0.04	0.55	1.34	4.48	0.03	1	46.9	27.4	37.01	23.24	70.14	23.66	1.47
pca.oclstr.km.nc2.e3	6.9	0.75	2.4	5.2	16.05	0.49	1.01	9.87	1.2	7.74	4.72	14.59	5.15	1.1
pca.oclstr.km.nc2.e4	12.86	2.15	4.06	7.03	26.86	1.95	1.02	4.02	0.2	3.2	2.07	6.09	1.96	0.98

Table D: continued

oclstr=ortho-clustering, fc = fuzzy c-means clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)
nc = no. clusters, Ica = data prepared using ICA, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
method of modeling	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.oclstr.km.nc2.e5	12.86	2.15	4.06	7.03	26.86	1.95	1.02	4.02	0.2	3.2	2.07	6.09	1.96	0.98
pca.oclstr.km.nc3.e1	1.37	0.03	0.47	0.98	3.09	0.19	1	32.01	10.31	22.7	2.44	34.45	29.57	1.32
pca.oclstr.km.nc3.e2	3.55	0.29	1.49	4.05	14.35	0.37	1	20.89	5.07	15.93	8.43	29.31	12.46	1.21
pca.oclstr.km.nc3.e3	3.55	0.29	1.49	4.05	14.35	0.37	1	20.89	5.07	15.93	8.43	29.31	12.46	1.21
pca.oclstr.km.nc3.e4	10.95	2.03	3.95	9.09	34.46	0.07	1.02	6.83	0.54	5.17	2.62	9.45	4.21	1.07
pca.oclstr.km.nc3.e5	10.95	2.03	3.95	9.09	34.46	0.07	1.02	6.83	0.54	5.17	2.62	9.45	4.21	1.07
pca.oclstr.km.nc4.e1	1.19	0.03	0.48	1.23	3.82	0	1	11.89	2.37	10.89	9.79	21.68	2.1	1.1
pca.oclstr.km.nc4.e2	2.09	0.08	0.78	1.87	5.45	0	1	11.97	2.38	10.91	9.74	21.71	2.23	1.12
pca.oclstr.km.nc4.e3	3.64	0.2	1.24	2.63	9.85	0	1	5.32	0.35	4.17	2.55	7.87	2.76	1.05
pca.oclstr.km.nc4.e4	9.65	1.76	3.68	9.12	34.27	0	1.02	4.5	0.2	3.2	0.37	4.87	4.14	1.05
pca.oclstr.km.nc4.e5	9.65	1.76	3.68	9.12	34.27	0	1.02	4.5	0.2	3.2	0.37	4.87	4.14	1.05
pca.oclstr.km.nc5.e1	1.31	0.03	0.46	1.01	3.7	0.04	1	66.18	44.11	46.96	5.55	71.73	60.63	0.94
pca.oclstr.km.nc5.e2	1.31	0.03	0.46	1.01	3.7	0.04	1	66.18	44.11	46.96	5.55	71.73	60.63	0.94
pca.oclstr.km.nc5.e3	2.68	0.11	0.91	1.88	7.55	0.41	1	61.52	38.24	43.73	6.23	67.75	55.29	0.94
pca.oclstr.km.nc5.e4	9.05	1.92	3.85	10.51	40.81	1.19	1.01	65.85	43.4	46.58	1.9	67.75	63.95	0.98
pca.oclstr.km.nc5.e5	9.05	1.92	3.85	10.51	40.81	1.19	1.01	65.85	43.4	46.58	1.9	67.75	63.95	0.98
pca.oclstr.kh.nc1.e1	1.49	0.04	0.55	1.3	4.98	0.01	1	54.55	44.67	47.26	38.62	93.17	15.93	1.55
pca.oclstr.kh.nc1.e2	5.29	0.44	1.85	4.04	15.75	0.38	1	26.69	13.56	26.04	25.37	52.06	1.32	1.27
pca.oclstr.kh.nc1.e3	6.26	0.6	2.15	4.56	12.51	0.44	1.01	20.61	6.67	18.26	15.57	36.18	5.04	1.21
pca.oclstr.kh.nc1.e4	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.kh.nc1.e5	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.kh.nc2.e1	225.63	567.7	66.08	76.56	413.03	122	3.26	252.88	669.69	182.99	54.96	307.84	197.92	3.53
pca.oclstr.kh.nc2.e2	225.63	567.7	66.08	76.56	413.03	122	3.26	252.88	669.69	182.99	54.96	307.84	197.92	3.53
pca.oclstr.kh.nc2.e3	225.63	567.7	66.08	76.56	413.03	122	3.26	252.88	669.69	182.99	54.96	307.84	197.92	3.53
pca.oclstr.kh.nc2.e4	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.kh.nc2.e5	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.kh.nc3.e1	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc3.e2	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc3.e3	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc3.e4	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.kh.nc3.e5	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.kh.nc4.e1	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc4.e2	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc4.e3	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36

Table D: continued

oclstr=ortho-clustering, kh=SOM clustering, km= k-means clustering, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)
nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

method of modeling	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
pca.oclstr.kh.nc4.e4	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.kh.nc4.e5	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.kh.nc5.e1	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc5.e2	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc5.e3	124.73	169.51	36.11	37.34	181.3	49.81	2.25	136.19	189.84	97.43	20.9	157.09	115.29	2.36
pca.oclstr.kh.nc5.e4	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.kh.nc5.e5	104.92	121.69	30.6	34.05	156.51	36.61	2.05	115.38	136.75	82.69	19.06	134.43	96.32	2.15
pca.oclstr.at.nc5.e1	1.49	0.04	0.55	1.3	4.98	0.01	1	54.55	44.67	47.26	38.62	93.17	15.93	1.55
pca.oclstr.at.nc5.e2	5.29	0.44	1.85	4.04	15.75	0.38	1	26.69	13.56	26.04	25.37	52.06	1.32	1.27
pca.oclstr.at.nc5.e3	6.26	0.6	2.15	4.56	12.51	0.44	1.01	20.61	6.67	18.26	15.57	36.18	5.04	1.21
pca.oclstr.at.nc5.e4	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.at.nc5.e5	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.fa.nc5.e1	1.49	0.04	0.55	1.3	4.98	0.01	1	54.55	44.67	47.26	38.62	93.17	15.93	1.55
pca.oclstr.fa.nc5.e2	5.29	0.44	1.85	4.04	15.75	0.38	1	26.69	13.56	26.04	25.37	52.08	1.32	1.27
pca.oclstr.fa.nc5.e3	6.26	0.6	2.15	4.56	12.51	0.44	1.01	20.61	6.67	18.26	15.57	36.18	5.04	1.21
pca.oclstr.fa.nc5.e4	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.oclstr.fa.nc5.e5	12.42	2.29	4.2	8.65	25.37	1.74	1.02	4.97	0.31	3.94	2.52	7.49	2.45	1.03
pca.autregrma.v1.pol	6.34	0.68	2.38	5.27	17.61	0.69	0.97	63.05	41.28	45.43	12.35	75.4	50.7	1.63
pca.autregrma.v1.sin	6.47	0.71	2.43	5.36	16.73	1.42	0.98	53.96	45.39	47.64	40.34	94.3	13.62	1.54
pca.autregrma.v1.tnh	6.83	0.72	2.45	5.07	15.94	1.62	0.98	53.85	57.98	53.84	53.83	107.68	0.02	1.54
pca.autregrma.v1.exp	2.31	0.06	0.69	0.63	3.52	1.11	0.98	5.25	0.38	4.39	3.3	8.55	1.95	0.95
pca.autregrma.v2.pol	6.95	0.92	2.77	6.63	24.02	0.25	1.01	48.72	33.86	41.15	31.83	80.55	16.89	1.32
pca.autregrma.v2.sin	6.82	0.85	2.66	6.18	22.63	0.24	1.01	56.72	53.65	51.79	46.34	103.06	10.38	1.46
pca.autregrma.v2.tnh	6.76	0.82	2.62	6.05	21.86	0.89	1.01	59.95	65.06	57.03	53.96	113.91	5.99	1.54
pca.autregrma.v2.exp	1.6	0.03	0.5	0.61	2.41	0.8	1.02	2	0.04	1.42	0.12	2.12	1.89	1
pca.autregrma.v3.pol	2.4	0.06	0.71	0.54	3.39	1.35	0.98	54.02	36.51	42.72	27.07	81.09	26.95	1.27
pca.autregrma.v3.sin	2.39	0.07	0.74	0.96	4.29	0.93	0.98	95.72	137.08	82.79	67.41	163.14	28.31	1.67
pca.autregrma.v3.tnh	2.39	0.07	0.77	1.23	4.81	0.86	0.98	111.05	201.28	100.32	88.3	199.35	22.74	1.88
pca.autregrma.v3.exp	2.39	0.06	0.69	0.05	2.46	2.29	0.98	7.3	0.53	5.16	0.07	7.37	7.23	1
pca.autregrma.v4.pol	2.37	0.06	0.7	0.57	3.26	1	0.98	54.74	37.61	43.36	27.66	82.39	27.08	1.28
pca.autregrma.v4.sin	2.37	0.06	0.72	0.83	4.17	0.57	0.98	97.47	142.6	84.44	68.99	166.46	28.47	1.69
pca.autregrma.v4.tnh	2.36	0.07	0.75	1.04	4.71	0.49	0.98	113.16	209.77	102.41	90.39	203.56	22.77	1.9
pca.autregrma.v4.exp	2.37	0.06	0.7	0.54	3.56	1.27	0.98	6.87	0.47	4.86	0.15	7.02	6.72	1
pca.autregrma.v5.pol	0.46	0	0.16	0.31	1.07	0.02	1	55.34	39.74	44.58	30.19	85.53	25.16	1.3

Table D: continued

oclstr=ortho-clustering, kh=SOM clustering,at=ART2, fa=fuzzy ART, e1=epsilon(0.001), e2=epsilon(0.005),e3=epsilon(0.01), e4=epsilon(0.05), e5=epsilon(0.1)
autregrma = ARMA, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic, exponential modeling functions
nc = no. clusters, ica = data prepared using ICA, mn error = mean error, ms error = mean squared error
rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.simplregr.v1.pol	1.17	0.02	0.09	1	6.73	0	1.01	1.16	0.02	0.32	0.84	3.16	0.22	1.01
box.simplregr.v1.sin	1.15	0.02	0.09	0.94	5.94	0	1.01	1.28	0.02	0.35	0.89	3.43	0	1.01
box.simplregr.v1.tnh	1.21	0.02	0.09	0.95	6.03	0	1.01	1.38	0.03	0.37	0.89	3.52	0.06	1.01
box.simplregr.v1.exp	1.19	0.02	0.1	1.02	5.94	0	1.01	1.12	0.02	0.34	1.01	3.56	0.02	1
box.simplregr.v2.pol	1.31	0.03	0.1	1.04	6.77	0	1.01	1.38	0.03	0.37	0.93	3.46	0.07	1.01
box.simplregr.v2.sin	1.3	0.03	0.1	0.99	6.06	0.01	1.01	1.6	0.03	0.41	0.89	3.73	0.3	1.02
box.simplregr.v2.tnh	1.35	0.03	0.1	1	6.15	0.01	1.01	1.72	0.04	0.43	0.91	3.83	0.13	1.02
box.simplregr.v2.exp	1.29	0.03	0.1	1.1	5.86	0.01	1.01	1.17	0.02	0.35	1.05	3.79	0.02	1.01
box.simplregr.v3.pol	0.86	0.01	0.06	0.57	4.7	0	0.99	0.87	0.01	0.23	0.58	2.21	0.01	0.99
box.simplregr.v3.sin	0.9	0.01	0.07	0.7	4.95	0	0.99	0.71	0.01	0.2	0.56	2.1	0.01	0.99
box.simplregr.v3.tnh	0.96	0.02	0.08	0.82	4.94	0	0.99	0.68	0.01	0.2	0.57	2.39	0.15	1
box.simplregr.v3.exp	1.09	0.02	0.08	0.68	3.59	0.01	0.99	1.19	0.02	0.3	0.66	2.64	0.01	0.99
box.simplregr.v4.pol	0.86	0.01	0.06	0.57	4.78	0	0.99	0.86	0.01	0.23	0.58	2.24	0.03	0.99
box.simplregr.v4.sin	0.9	0.01	0.07	0.7	5.03	0	0.99	0.7	0.01	0.2	0.55	2.04	0.01	0.99
box.simplregr.v4.tnh	0.96	0.02	0.08	0.83	5.02	0	0.99	0.67	0.01	0.2	0.56	2.34	0.13	1
box.simplregr.v4.exp	1.08	0.02	0.08	0.68	3.66	0	0.99	1.19	0.02	0.3	0.66	2.67	0.08	0.99
box.simplregr.v5.pol	0.48	0	0.04	0.47	3.94	0	1	0.48	0	0.13	0.35	1.44	0.03	1
box.simplregr.v5.sin	0.6	0.01	0.05	0.57	4.19	0	1	0.55	0	0.15	0.39	1.33	0.01	1
box.simplregr.v5.tnh	0.73	0.01	0.06	0.68	4.18	0	1	0.66	0.01	0.18	0.44	1.62	0.13	1
box.simplregr.v5.exp	0.79	0.01	0.06	0.66	3.53	0	1	0.58	0.01	0.17	0.53	1.87	0.01	1
box.cr.fc.v1.pol.nc2	1.06	0.02	0.09	0.94	5.47	0	1.01	1.34	0.02	0.34	0.71	3.04	0.16	1.01
box.cr.fc.v1.pol.nc3	1.04	0.02	0.08	0.9	5.03	0	1.01	0.81	0.01	0.22	0.58	2.3	0.06	1
box.cr.fc.v1.pol.nc4	0.94	0.02	0.08	0.83	4.6	0	1.01	0.95	0.01	0.26	0.7	2.3	0.01	1.01
box.cr.fc.v1.pol.nc5	0.94	0.02	0.08	0.87	4.49	0.01	1.01	0.9	0.01	0.25	0.7	2.58	0.08	1.01
box.cr.fc.v1.sin.nc2	1.05	0.02	0.08	0.9	4.99	0	1.01	1.32	0.02	0.34	0.75	3.16	0.04	1.01
box.cr.fc.v1.sin.nc3	1.03	0.02	0.08	0.84	5.37	0	1.01	0.81	0.01	0.21	0.5	2.44	0.24	1
box.cr.fc.v1.sin.nc4	0.94	0.02	0.08	0.81	5.31	0	1.01	0.81	0.01	0.22	0.58	2.24	0.07	1.01
box.cr.fc.v1.sin.nc5	0.94	0.02	0.08	0.83	4.44	0	1.01	0.8	0.01	0.22	0.61	2.14	0.08	1.01
box.cr.fc.v1.tnh.nc2	1.05	0.02	0.08	0.9	4.97	0	1.01	1.34	0.02	0.35	0.78	3.23	0.08	1.01
box.cr.fc.v1.tnh.nc3	1.02	0.02	0.08	0.83	5.19	0	1.01	0.93	0.01	0.25	0.58	2.6	0.28	1.01
box.cr.fc.v1.tnh.nc4	0.96	0.02	0.08	0.81	5.41	0	1.01	0.74	0.01	0.21	0.6	2.02	0	1
box.cr.fc.v1.tnh.nc5	0.92	0.01	0.07	0.79	4.31	0	1.01	0.79	0.01	0.22	0.63	2.5	0.04	1.01
box.cr.fc.v1.exp.nc2	1.01	0.02	0.08	0.76	4.27	0.01	1	1.29	0.02	0.35	0.91	3.26	0.03	1.01
box.cr.fc.v1.exp.nc3	0.92	0.01	0.07	0.77	4.65	0	1	1.26	0.02	0.35	0.9	2.99	0.07	1.01

Table E: performance statistics of all models on problem of modeling of Box Jenkins' gas Furnace

* simplregr = simple rigression, cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.cr.fc.v1.exp.nc4	0.82	0.01	0.06	0.63	2.83	0.01	1.01	1.15	0.03	0.38	1.24	3.86	0.03	1.01
box.cr.fc.v1.exp.nc5	0.81	0.01	0.06	0.61	2.53	0	1.01	0.97	0.02	0.3	0.92	2.84	0.03	1.01
box.cr.fc.v2.pol.nc2	1.21	0.02	0.1	1.02	5.65	0.01	1.01	1.59	0.03	0.4	0.79	3.29	0.03	1.02
box.cr.fc.v2.pol.nc3	1.21	0.02	0.09	0.96	5.29	0.01	1.01	0.99	0.01	0.27	0.66	2.65	0.02	1.01
box.cr.fc.v2.pol.nc4	1.17	0.02	0.09	0.87	4.88	0	1.01	1.25	0.02	0.32	0.71	2.64	0.14	1.01
box.cr.fc.v2.pol.nc5	1.17	0.02	0.09	0.9	4.79	0.04	1.01	1.18	0.02	0.31	0.69	2.9	0.31	1.01
box.cr.fc.v2.sin.nc2	1.2	0.02	0.09	0.99	5.19	0	1.01	1.6	0.03	0.4	0.77	3.41	0.26	1.02
box.cr.fc.v2.sin.nc3	1.22	0.02	0.09	0.9	5.6	0.02	1.01	0.99	0.01	0.27	0.71	2.82	0.05	1.01
box.cr.fc.v2.sin.nc4	1.16	0.02	0.09	0.87	5.57	0	1.01	1.09	0.02	0.28	0.63	2.57	0.21	1.01
box.cr.fc.v2.sin.nc5	1.16	0.02	0.09	0.89	4.74	0	1.01	1.09	0.02	0.28	0.63	2.48	0.14	1.01
box.cr.fc.v2.tnh.nc2	1.21	0.02	0.1	0.99	5.16	0	1.01	1.59	0.03	0.4	0.82	3.48	0.36	1.01
box.cr.fc.v2.tnh.nc3	1.23	0.02	0.09	0.89	5.43	0	1.01	1.17	0.02	0.31	0.78	2.97	0.04	1.01
box.cr.fc.v2.tnh.nc4	1.18	0.02	0.09	0.86	5.67	0	1.01	0.98	0.01	0.26	0.59	2.34	0.07	1.01
box.cr.fc.v2.tnh.nc5	1.16	0.02	0.09	0.85	4.63	0	1.01	1.06	0.02	0.28	0.67	2.83	0.14	1.01
box.cr.fc.v2.exp.nc2	1.17	0.02	0.09	0.84	4.38	0.01	1.01	1.51	0.03	0.4	0.94	3.45	0.11	1.01
box.cr.fc.v2.exp.nc3	1.12	0.02	0.08	0.82	4.74	0	1.01	1.49	0.03	0.4	0.95	3.28	0.09	1.01
box.cr.fc.v2.exp.nc4	1.08	0.02	0.08	0.69	3.08	0	1.01	1.37	0.03	0.41	1.19	4.07	0.18	1.01
box.cr.fc.v2.exp.nc5	1.06	0.02	0.08	0.7	2.97	0	1.01	1.2	0.02	0.33	0.9	3.13	0.12	1.01
box.cr.fc.v3.pol.nc2	0.86	0.01	0.06	0.56	4.42	0	0.99	0.91	0.01	0.24	0.6	2.25	0.1	0.99
box.cr.fc.v3.pol.nc3	0.85	0.01	0.06	0.56	4.09	0.01	0.99	1.01	0.01	0.27	0.63	2.3	0.02	0.99
box.cr.fc.v3.pol.nc4	0.85	0.01	0.06	0.55	4.07	0	0.99	0.92	0.01	0.24	0.55	2.05	0.06	0.99
box.cr.fc.v3.pol.nc5	0.85	0.01	0.06	0.54	4.05	0.01	0.99	1.01	0.01	0.26	0.57	2.32	0.11	0.99
box.cr.fc.v3.sin.nc2	0.9	0.01	0.07	0.64	4.45	0.01	0.99	0.78	0.01	0.21	0.56	2.16	0.01	0.99
box.cr.fc.v3.sin.nc3	0.87	0.01	0.06	0.6	3.97	0	0.99	0.89	0.01	0.24	0.6	2.34	0.06	0.99
box.cr.fc.v3.sin.nc4	0.85	0.01	0.06	0.56	3.86	0.02	0.99	0.75	0.01	0.21	0.56	2.25	0.05	0.99
box.cr.fc.v3.sin.nc5	0.85	0.01	0.06	0.56	3.89	0.01	0.99	0.94	0.01	0.25	0.62	2.25	0.06	0.99
box.cr.fc.v3.tnh.nc2	0.93	0.01	0.07	0.72	4.26	0.01	0.99	0.76	0.01	0.2	0.46	1.95	0.1	0.99
box.cr.fc.v3.tnh.nc3	0.89	0.01	0.07	0.65	3.85	0	0.99	0.8	0.01	0.22	0.6	2.21	0	0.99
box.cr.fc.v3.tnh.nc4	0.86	0.01	0.06	0.59	3.75	0	0.99	0.87	0.02	0.28	0.89	3.87	0.01	0.99
box.cr.fc.v3.tnh.nc5	0.85	0.01	0.06	0.57	3.77	0	0.99	0.9	0.01	0.24	0.6	2.22	0.09	0.99
box.cr.fc.v3.exp.nc2	0.95	0.01	0.07	0.59	4.16	0.01	0.99	1.03	0.01	0.26	0.54	2.1	0.24	0.99
box.cr.fc.v3.exp.nc3	0.89	0.01	0.06	0.56	3.98	0.01	0.99	1.04	0.02	0.27	0.65	2.47	0.08	0.99
box.cr.fc.v3.exp.nc4	0.85	0.01	0.06	0.55	4.24	0	0.99	1.08	0.01	0.27	0.56	2.21	0.28	0.99
box.cr.fc.v3.exp.nc5	0.86	0.01	0.06	0.54	4.31	0.02	0.99	1.11	0.02	0.28	0.59	2.41	0.23	0.99

Table E: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box Gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.cr.fc.v4.pol.nc2	0.86	0.01	0.06	0.56	4.47	0	0.99	0.92	0.01	0.25	0.6	2.3	0.11	0.99
box.cr.fc.v4.pol.nc3	0.85	0.01	0.06	0.56	4.12	0.02	0.99	1.01	0.01	0.27	0.63	2.33	0.06	0.99
box.cr.fc.v4.pol.nc4	0.85	0.01	0.06	0.55	4.1	0	0.99	0.92	0.01	0.24	0.55	2.06	0.06	0.99
box.cr.fc.v4.pol.nc5	0.85	0.01	0.06	0.54	4.08	0.01	0.99	1.01	0.01	0.26	0.58	2.33	0.11	0.99
box.cr.fc.v4.sin.nc2	0.9	0.01	0.07	0.64	4.5	0	0.99	0.79	0.01	0.22	0.56	2.21	0.02	0.99
box.cr.fc.v4.sin.nc3	0.87	0.01	0.06	0.61	4	0.01	0.99	0.9	0.01	0.24	0.61	2.38	0.07	0.99
box.cr.fc.v4.sin.nc4	0.85	0.01	0.06	0.56	3.89	0.01	0.99	0.76	0.01	0.21	0.57	2.29	0.06	0.99
box.cr.fc.v4.sin.nc5	0.85	0.01	0.06	0.56	3.92	0	0.99	0.94	0.01	0.25	0.63	2.26	0.06	0.99
box.cr.fc.v4.tnh.nc2	0.93	0.01	0.07	0.72	4.31	0.01	0.99	0.76	0.01	0.2	0.47	2	0.08	0.99
box.cr.fc.v4.tnh.nc3	0.89	0.01	0.07	0.66	3.88	0.01	0.99	0.8	0.01	0.22	0.61	2.25	0.01	0.99
box.cr.fc.v4.tnh.nc4	0.86	0.01	0.06	0.59	3.77	0	0.99	0.88	0.02	0.28	0.91	3.97	0.02	0.99
box.cr.fc.v4.tnh.nc5	0.85	0.01	0.06	0.57	3.79	0.01	0.99	0.9	0.01	0.24	0.61	2.3	0.09	0.99
box.cr.fc.v4.exp.nc2	0.94	0.01	0.07	0.59	4.21	0	0.99	1.05	0.01	0.26	0.54	2.1	0.27	0.99
box.cr.fc.v4.exp.nc3	0.89	0.01	0.06	0.56	4.02	0.02	0.99	1.03	0.01	0.27	0.66	2.48	0.07	0.99
box.cr.fc.v4.exp.nc4	0.85	0.01	0.06	0.55	4.27	0	0.99	1.08	0.01	0.27	0.57	2.22	0.29	0.99
box.cr.fc.v4.exp.nc5	0.86	0.01	0.06	0.54	4.35	0	0.99	1.1	0.02	0.28	0.6	2.4	0.19	0.99
box.cr.fc.v5.pol.nc2	0.48	0	0.04	0.47	3.66	0	1	0.49	0	0.14	0.37	1.47	0.02	1
box.cr.fc.v5.pol.nc3	0.49	0	0.04	0.44	3.33	0	1	0.57	0	0.15	0.38	1.52	0.02	1
box.cr.fc.v5.pol.nc4	0.47	0	0.04	0.44	3.31	0	1	0.44	0	0.13	0.36	1.27	0.07	1
box.cr.fc.v5.pol.nc5	0.47	0	0.04	0.43	3.29	0.01	1	0.47	0	0.14	0.45	1.54	0.01	1
box.cr.fc.v5.sin.nc2	0.57	0.01	0.05	0.53	3.69	0	1	0.51	0	0.14	0.38	1.38	0	1
box.cr.fc.v5.sin.nc3	0.54	0.01	0.04	0.48	3.21	0	1	0.56	0	0.16	0.41	1.56	0.03	1
box.cr.fc.v5.sin.nc4	0.49	0	0.04	0.43	3.1	0	1	0.5	0	0.14	0.4	1.48	0.02	1
box.cr.fc.v5.sin.nc5	0.49	0	0.04	0.43	3.13	0	1	0.5	0	0.15	0.45	1.47	0.04	1
box.cr.fc.v5.tnh.nc2	0.66	0.01	0.05	0.58	3.5	0.01	1	0.5	0	0.16	0.49	1.64	0.01	1
box.cr.fc.v5.tnh.nc3	0.6	0.01	0.05	0.51	3.09	0	1	0.59	0.01	0.17	0.46	1.7	0.02	1
box.cr.fc.v5.tnh.nc4	0.53	0	0.04	0.44	2.98	0	1	0.66	0.01	0.21	0.68	3.11	0	1
box.cr.fc.v5.tnh.nc5	0.5	0	0.04	0.44	3.01	0	1	0.48	0	0.15	0.46	1.45	0.04	1
box.cr.fc.v5.exp.nc2	0.6	0.01	0.05	0.53	3.4	0	1	0.51	0	0.15	0.44	1.38	0	1
box.cr.fc.v5.exp.nc3	0.53	0	0.04	0.46	3.22	0	1	0.59	0.01	0.16	0.4	1.69	0.1	1
box.cr.fc.v5.exp.nc4	0.49	0	0.04	0.43	3.48	0.01	1	0.52	0	0.15	0.44	1.44	0.08	1
box.cr.fc.v5.exp.nc5	0.49	0	0.04	0.43	3.55	0	1	0.52	0	0.16	0.48	1.64	0.01	1
box.cr.km.v1.pol.nc2	1.07	0.02	0.09	0.92	4.86	0.02	1.01	1.44	0.03	0.36	0.76	3.19	0.07	1.01
box.cr.km.v1.pol.nc3	1.05	0.02	0.08	0.92	5.39	0	1.01	0.82	0.01	0.22	0.54	2.12	0.02	1.01

Table E: continued

cr = cluster wise regression, fc = fuzzy c-means clustering, km=k-mean clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box Gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.cr.km.v1.pol.nc4	0.98	0.02	0.08	0.84	4.46	0.01	1.01	0.87	0.01	0.23	0.57	2.29	0.16	1.01
box.cr.km.v1.pol.nc5	0.96	0.02	0.08	0.88	4.59	0.01	1.01	0.87	0.01	0.25	0.7	2.6	0	1.01
box.cr.km.v1.sin.nc2	1.05	0.02	0.08	0.89	4.64	0	1.01	1.4	0.03	0.36	0.78	3.28	0.18	1.01
box.cr.km.v1.sin.nc3	1.02	0.02	0.08	0.87	5.17	0.01	1.01	0.91	0.01	0.24	0.55	2.37	0.03	1.01
box.cr.km.v1.sin.nc4	0.96	0.02	0.08	0.8	4.34	0.01	1.01	1.08	0.02	0.28	0.68	2.83	0.24	1.01
box.cr.km.v1.sin.nc5	0.94	0.02	0.08	0.83	4.38	0	1.01	0.76	0.01	0.22	0.61	2.11	0.06	1.01
box.cr.km.v1.tnh.nc2	1.06	0.02	0.08	0.9	4.72	0.01	1.01	1.47	0.03	0.37	0.78	3.34	0.02	1.01
box.cr.km.v1.tnh.nc3	1.01	0.02	0.08	0.87	5.13	0	1.01	1.02	0.01	0.26	0.58	2.55	0.1	1.01
box.cr.km.v1.tnh.nc4	0.96	0.02	0.08	0.8	4.75	0.01	1.01	0.94	0.01	0.24	0.53	2.4	0.27	1.01
box.cr.km.v1.tnh.nc5	0.95	0.02	0.08	0.81	4.17	0	1.01	0.81	0.01	0.22	0.58	2.16	0.23	1.01
box.cr.km.v1.exp.nc2	1.04	0.02	0.08	0.78	3.9	0	1.01	1.22	0.02	0.34	0.91	3.28	0.12	1.01
box.cr.km.v1.exp.nc3	0.91	0.01	0.07	0.76	4.72	0.01	1	1.25	0.02	0.34	0.84	2.86	0.03	1.01
box.cr.km.v1.exp.nc4	0.84	0.01	0.06	0.65	2.89	0	1.01	0.8	0.01	0.24	0.69	2.18	0.06	1.01
box.cr.km.v1.exp.nc5	0.82	0.01	0.06	0.62	2.97	0	1.01	0.65	0.01	0.19	0.56	1.89	0.02	1.01
box.cr.km.v2.pol.nc2	1.21	0.02	0.1	1.02	5.07	0	1.01	1.67	0.03	0.42	0.82	3.42	0.01	1.02
box.cr.km.v2.pol.nc3	1.23	0.02	0.1	0.96	5.61	0	1.01	1.11	0.02	0.29	0.64	2.47	0.13	1.01
box.cr.km.v2.pol.nc4	1.19	0.02	0.09	0.89	4.74	0	1.01	1.16	0.02	0.3	0.65	2.64	0.14	1.01
box.cr.km.v2.pol.nc5	1.19	0.02	0.09	0.91	4.88	0.02	1.01	1.17	0.02	0.3	0.68	2.91	0.23	1.01
box.cr.km.v2.sin.nc2	1.2	0.02	0.09	0.99	4.82	0.01	1.01	1.62	0.03	0.41	0.87	3.52	0.08	1.02
box.cr.km.v2.sin.nc3	1.23	0.02	0.09	0.91	5.39	0.02	1.01	1.21	0.02	0.31	0.67	2.73	0.02	1.01
box.cr.km.v2.sin.nc4	1.18	0.02	0.09	0.86	4.63	0.01	1.01	1.39	0.03	0.36	0.78	3.16	0.13	1.01
box.cr.km.v2.sin.nc5	1.17	0.02	0.09	0.88	4.68	0.02	1.01	1.07	0.02	0.28	0.67	2.45	0.08	1.01
box.cr.km.v2.tnh.nc2	1.21	0.02	0.1	1	4.91	0	1.01	1.68	0.04	0.42	0.87	3.59	0.08	1.02
box.cr.km.v2.tnh.nc3	1.23	0.02	0.09	0.91	5.37	0	1.01	1.28	0.02	0.33	0.76	2.91	0.06	1.01
box.cr.km.v2.tnh.nc4	1.19	0.02	0.09	0.85	5.02	0	1.01	1.22	0.02	0.31	0.68	2.81	0.1	1.01
box.cr.km.v2.tnh.nc5	1.17	0.02	0.09	0.87	4.49	0.02	1.01	1.08	0.02	0.29	0.7	2.5	0.03	1.01
box.cr.km.v2.exp.nc2	1.2	0.02	0.09	0.87	4.14	0.01	1.01	1.4	0.03	0.38	0.96	3.48	0.04	1.01
box.cr.km.v2.exp.nc3	1.12	0.02	0.08	0.82	4.84	0	1.01	1.51	0.03	0.39	0.88	3.08	0.14	1.01
box.cr.km.v2.exp.nc4	1.09	0.02	0.08	0.7	3.16	0.01	1.01	1.05	0.02	0.28	0.7	2.45	0	1.01
box.cr.km.v2.exp.nc5	1.08	0.02	0.08	0.68	3.23	0	1.01	0.98	0.01	0.26	0.59	2.21	0.1	1.01
box.cr.km.v3.pol.nc2	0.86	0.01	0.06	0.56	4.44	0.01	0.99	0.97	0.01	0.26	0.61	2.31	0.17	0.99
box.cr.km.v3.pol.nc3	0.85	0.01	0.06	0.55	4.14	0.03	0.99	0.96	0.01	0.26	0.63	2.61	0.06	0.99
box.cr.km.v3.pol.nc4	0.85	0.01	0.06	0.55	4.17	0.01	0.99	0.95	0.01	0.25	0.55	2.17	0.08	0.99
box.cr.km.v3.pol.nc5	0.85	0.01	0.06	0.55	4.09	0	0.99	0.99	0.01	0.26	0.58	2.37	0.13	0.99

Table E: continued

cr = cluster wise regression, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5   pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box Gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.cr.km.v3.sin.nc2	0.9	0.01	0.07	0.64	4.43	0	0.99	0.75	0.01	0.21	0.54	2.08	0.01	0.99
box.cr.km.v3.sin.nc3	0.87	0.01	0.06	0.61	4.11	0	0.99	0.84	0.01	0.23	0.63	2.61	0.15	0.99
box.cr.km.v3.sin.nc4	0.87	0.01	0.06	0.59	3.99	0.01	0.99	0.82	0.01	0.22	0.52	2.07	0.2	0.99
box.cr.km.v3.sin.nc5	0.85	0.01	0.06	0.56	4.02	0.01	0.99	0.98	0.01	0.25	0.53	2.19	0.05	0.99
box.cr.km.v3.tnh.nc2	0.94	0.01	0.07	0.72	4.31	0.01	0.99	0.75	0.01	0.2	0.47	1.84	0.24	0.99
box.cr.km.v3.tnh.nc3	0.88	0.01	0.07	0.65	3.96	0	0.99	0.79	0.01	0.23	0.65	2.48	0.02	0.99
box.cr.km.v3.tnh.nc4	0.87	0.01	0.06	0.61	3.86	0.01	0.99	0.8	0.01	0.23	0.62	2.3	0.04	0.99
box.cr.km.v3.tnh.nc5	0.86	0.01	0.06	0.58	3.88	0	0.99	0.96	0.01	0.24	0.52	2.11	0.03	0.99
box.cr.km.v3.exp.nc2	0.96	0.01	0.07	0.61	4.26	0	0.99	1.17	0.02	0.29	0.57	2.21	0.41	0.99
box.cr.km.v3.exp.nc3	0.9	0.01	0.06	0.57	4.01	0.01	0.99	1.01	0.01	0.27	0.65	2.33	0.02	0.99
box.cr.km.v3.exp.nc4	0.86	0.01	0.06	0.55	4.12	0	0.99	1.06	0.01	0.27	0.59	2.22	0.2	0.99
box.cr.km.v3.exp.nc5	0.85	0.01	0.06	0.55	3.73	0	0.99	1.02	0.01	0.26	0.54	2.25	0.26	0.99
box.cr.km.v4.pol.nc2	0.86	0.01	0.06	0.56	4.49	0	0.99	0.99	0.01	0.26	0.61	2.36	0.2	0.99
box.cr.km.v4.pol.nc3	0.85	0.01	0.06	0.55	4.18	0	0.99	0.98	0.01	0.26	0.64	2.66	0.06	0.99
box.cr.km.v4.pol.nc4	0.85	0.01	0.06	0.55	4.21	0.01	0.99	0.94	0.01	0.24	0.55	2.17	0.08	0.99
box.cr.km.v4.pol.nc5	0.85	0.01	0.06	0.55	4.12	0.01	0.99	0.99	0.01	0.26	0.58	2.37	0.1	0.99
box.cr.km.v4.sin.nc2	0.91	0.01	0.07	0.64	4.49	0.01	0.99	0.76	0.01	0.21	0.55	2.13	0.02	0.99
box.cr.km.v4.sin.nc3	0.87	0.01	0.06	0.61	4.14	0	0.99	0.85	0.01	0.24	0.64	2.66	0.15	0.99
box.cr.km.v4.sin.nc4	0.87	0.01	0.06	0.59	4.02	0	0.99	0.81	0.01	0.22	0.52	2.07	0.2	0.99
box.cr.km.v4.sin.nc5	0.85	0.01	0.06	0.56	4.05	0	0.99	0.98	0.01	0.25	0.52	2.19	0.05	0.99
box.cr.km.v4.tnh.nc2	0.94	0.01	0.07	0.72	4.36	0	0.99	0.75	0.01	0.2	0.47	1.88	0.23	0.99
box.cr.km.v4.tnh.nc3	0.89	0.01	0.07	0.65	3.99	0.02	0.99	0.8	0.01	0.23	0.66	2.53	0.02	0.99
box.cr.km.v4.tnh.nc4	0.87	0.01	0.07	0.61	3.89	0	0.99	0.8	0.01	0.23	0.62	2.35	0.06	0.99
box.cr.km.v4.tnh.nc5	0.86	0.01	0.06	0.58	3.91	0	0.99	0.95	0.01	0.24	0.52	2.1	0.03	0.99
box.cr.km.v4.exp.nc2	0.96	0.01	0.07	0.61	4.31	0	0.99	1.18	0.02	0.29	0.57	2.25	0.36	0.99
box.cr.km.v4.exp.nc3	0.9	0.01	0.06	0.57	4.05	0	0.99	1	0.01	0.27	0.66	2.35	0.05	0.99
box.cr.km.v4.exp.nc4	0.86	0.01	0.06	0.55	4.15	0	0.99	1.05	0.01	0.27	0.6	2.22	0.15	0.99
box.cr.km.v4.exp.nc5	0.85	0.01	0.06	0.55	3.77	0.01	0.99	1.02	0.01	0.26	0.53	2.25	0.27	0.99
box.cr.km.v5.pol.nc2	0.48	0	0.04	0.47	3.68	0	1	0.51	0	0.14	0.39	1.54	0.03	1
box.cr.km.v5.pol.nc3	0.47	0	0.04	0.44	3.38	0	1	0.53	0	0.15	0.41	1.83	0.14	1
box.cr.km.v5.pol.nc4	0.47	0	0.04	0.44	3.41	0	1	0.46	0	0.13	0.37	1.39	0.09	1
box.cr.km.v5.pol.nc5	0.47	0	0.04	0.43	3.33	0	1	0.51	0	0.14	0.39	1.6	0.09	1
box.cr.km.v5.sin.nc2	0.58	0.01	0.05	0.54	3.68	0.01	1	0.5	0	0.14	0.39	1.31	0.02	1
box.cr.km.v5.sin.nc3	0.53	0.01	0.04	0.48	3.34	0	1	0.55	0.01	0.16	0.45	1.84	0.02	1

Table E: continued

cr = cluster wise regression, km=k-means clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box Gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics							prediction statistics						
Method	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.cr.km.v5.sin.nc4	0.52	0	0.04	0.47	3.23	0	1	0.49	0	0.14	0.39	1.54	0.02	1
box.cr.km.v5.sin.nc5	0.49	0	0.04	0.44	3.26	0.01	1	0.49	0	0.14	0.36	1.42	0.05	1
box.cr.km.v5.tnh.nc2	0.68	0.01	0.05	0.59	3.55	0	1	0.56	0.01	0.17	0.5	1.7	0	1
box.cr.km.v5.tnh.nc3	0.58	0.01	0.05	0.51	3.2	0	1	0.63	0.01	0.17	0.44	1.7	0.05	1
box.cr.km.v5.tnh.nc4	0.55	0.01	0.04	0.48	3.1	0	1	0.57	0.01	0.17	0.47	1.79	0.03	1
box.cr.km.v5.tnh.nc5	0.51	0	0.04	0.45	3.12	0	1	0.49	0	0.14	0.37	1.33	0	1
box.cr.km.v5.exp.nc2	0.64	0.01	0.05	0.53	3.5	0	1	0.56	0.01	0.16	0.48	1.44	0.01	1
box.cr.km.v5.exp.nc3	0.55	0.01	0.04	0.48	3.24	0	1	0.58	0	0.16	0.38	1.56	0.01	1
box.cr.km.v5.exp.nc4	0.5	0	0.04	0.43	3.36	0.01	1	0.52	0	0.15	0.4	1.44	0.06	1
box.cr.km.v5.exp.nc5	0.5	0	0.04	0.41	2.96	0	1	0.48	0	0.13	0.35	1.47	0.05	1
box.cr.kh.v1.pol.nc2	1.65	0.04	0.13	1.27	5.71	0	1.01	2.36	0.07	0.61	1.36	5.19	0.31	1.01
box.cr.kh.v1.pol.nc3	1.69	0.04	0.13	1.24	6.02	0	1.01	2.13	0.07	0.57	1.41	4.92	0.22	1.01
box.cr.kh.v1.pol.nc4	1.65	0.04	0.12	1.21	5.61	0.01	1.01	2.47	0.08	0.62	1.29	4.65	0.17	1.01
box.cr.kh.v1.pol.nc5	1.65	0.04	0.12	1.2	5.54	0	1.01	2.39	0.07	0.59	1.12	4.07	0.42	1.01
box.cr.kh.v1.sin.nc2	1.68	0.04	0.13	1.28	6.25	0	1.01	2.34	0.07	0.61	1.39	5.08	0.42	1.01
box.cr.kh.v1.sin.nc3	1.71	0.04	0.13	1.19	6.41	0.02	1.01	1.88	0.06	0.53	1.42	4.77	0.01	1.01
box.cr.kh.v1.sin.nc4	1.7	0.04	0.13	1.22	5.96	0.02	1.01	2.17	0.07	0.58	1.43	4.62	0.15	1.01
box.cr.kh.v1.sin.nc5	1.64	0.04	0.13	1.27	5.87	0	1.01	2.37	0.07	0.6	1.3	4.56	0.41	1.01
box.cr.kh.v1.tnh.nc2	1.75	0.05	0.13	1.3	6.49	0.01	1.01	2.32	0.07	0.61	1.43	5.01	0.43	1.01
box.cr.kh.v1.tnh.nc3	1.78	0.05	0.13	1.26	6.37	0	1.01	1.89	0.06	0.53	1.42	4.84	0.02	1.01
box.cr.kh.v1.tnh.nc4	1.73	0.05	0.13	1.24	6.16	0.02	1.01	2.2	0.07	0.59	1.45	4.8	0.02	1.01
box.cr.kh.v1.tnh.nc5	1.68	0.04	0.13	1.24	6.15	0	1.01	2.39	0.07	0.61	1.28	4.6	0.17	1.01
box.cr.kh.v1.exp.nc2	1.53	0.04	0.12	1.15	5.83	0.01	1.01	2.01	0.06	0.53	1.22	4.38	0.31	1
box.cr.kh.v1.exp.nc3	1.59	0.04	0.12	1.2	5.42	0	1.01	1.99	0.05	0.52	1.17	4.11	0.53	1
box.cr.kh.v1.exp.nc4	1.55	0.04	0.12	1.17	5.82	0.01	1.01	2.23	0.07	0.57	1.26	4.69	0.43	1
box.cr.kh.v1.exp.nc5	1.54	0.04	0.12	1.13	5.92	0.01	1.01	2.16	0.06	0.57	1.35	4.43	0.12	1
box.cr.kh.v2.pol.nc2	1.8	0.05	0.14	1.31	5.9	0.01	1.01	2.59	0.08	0.65	1.27	5.56	0.66	1.01
box.cr.kh.v2.pol.nc3	1.81	0.05	0.14	1.31	6.5	0.01	1.01	2.37	0.07	0.61	1.3	5.3	0.63	1.01
box.cr.kh.v2.pol.nc4	1.8	0.05	0.13	1.25	6.11	0.02	1.01	2.64	0.09	0.66	1.31	5.03	0.08	1.01
box.cr.kh.v2.pol.nc5	1.78	0.05	0.13	1.26	5.91	0.01	1.01	2.56	0.08	0.63	1.19	4.47	0.04	1.01
box.cr.kh.v2.sin.nc2	1.82	0.05	0.14	1.33	5.99	0	1.01	2.58	0.08	0.64	1.28	5.46	0.81	1.01
box.cr.kh.v2.sin.nc3	1.84	0.05	0.14	1.26	6.89	0.01	1.01	2.12	0.06	0.55	1.29	5.14	0.32	1.01
box.cr.kh.v2.sin.nc4	1.83	0.05	0.14	1.29	6.46	0.01	1.01	2.4	0.08	0.62	1.35	4.99	0.16	1.01
box.cr.kh.v2.sin.nc5	1.8	0.05	0.14	1.31	5.41	0.04	1.01	2.58	0.08	0.65	1.28	4.99	0.24	1.01

Table E: continued

cr = cluster wise regression, km=k-means clustering, kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box Gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.cr.kh.v2.tnh.nc2	1.91	0.05	0.14	1.34	6.04	0.02	1.01	2.56	0.08	0.64	1.3	5.4	0.83	1.01
box.cr.kh.v2.tnh.nc3	1.92	0.05	0.14	1.31	6.85	0.01	1.01	2.14	0.06	0.56	1.26	5.22	0.37	1.01
box.cr.kh.v2.tnh.nc4	1.88	0.05	0.14	1.29	6.54	0.03	1.01	2.45	0.08	0.63	1.35	4.98	0.36	1.01
box.cr.kh.v2.tnh.nc5	1.85	0.05	0.14	1.26	5.7	0.04	1.01	2.6	0.08	0.65	1.25	4.42	0.19	1.01
box.cr.kh.v2.exp.nc2	1.67	0.04	0.13	1.25	6.29	0.02	1.01	2.14	0.06	0.53	1.05	4.06	0.75	1
box.cr.kh.v2.exp.nc3	1.72	0.05	0.13	1.29	5.91	0.01	1.01	2.12	0.06	0.53	1.1	4.53	0.21	1.01
box.cr.kh.v2.exp.nc4	1.69	0.04	0.13	1.26	6.31	0.01	1.01	2.36	0.07	0.58	1.05	4.23	0.53	1
box.cr.kh.v2.exp.nc5	1.65	0.04	0.13	1.26	6.42	0	1.01	2.22	0.07	0.58	1.32	4.76	0.15	1
box.cr.kh.v3.pol.nc2	1.46	0.04	0.12	1.22	6.21	0	0.99	1.85	0.06	0.56	1.69	5.44	0.13	0.99
box.cr.kh.v3.pol.nc3	1.44	0.04	0.11	1.21	7.37	0	0.99	1.81	0.06	0.54	1.63	5.13	0.01	0.99
box.cr.kh.v3.pol.nc4	1.36	0.03	0.11	1.15	7.04	0	0.99	2.07	0.07	0.6	1.71	5.45	0.08	0.99
box.cr.kh.v3.pol.nc5	1.41	0.03	0.11	1.19	6.63	0	0.99	1.85	0.06	0.53	1.49	4.98	0.22	0.99
box.cr.kh.v3.sin.nc2	1.49	0.04	0.12	1.33	6.99	0	0.99	1.84	0.06	0.57	1.75	5.85	0.08	0.99
box.cr.kh.v3.sin.nc3	1.48	0.04	0.12	1.28	8.01	0.01	0.99	1.8	0.06	0.54	1.61	5.42	0.03	0.99
box.cr.kh.v3.sin.nc4	1.47	0.04	0.12	1.3	8.54	0.01	0.99	1.79	0.06	0.53	1.57	5.51	0.01	0.99
box.cr.kh.v3.sin.nc5	1.45	0.04	0.12	1.28	7.45	0.01	0.99	1.82	0.06	0.53	1.55	5.49	0.33	0.99
box.cr.kh.v3.tnh.nc2	1.57	0.04	0.13	1.4	7.32	0.03	0.99	1.84	0.07	0.57	1.8	6.07	0.04	0.99
box.cr.kh.v3.tnh.nc3	1.56	0.04	0.13	1.38	8.23	0	0.99	1.84	0.06	0.55	1.63	5.71	0.42	0.99
box.cr.kh.v3.tnh.nc4	1.51	0.04	0.12	1.35	8.91	0	0.99	1.78	0.06	0.54	1.63	5.82	0.02	0.99
box.cr.kh.v3.tnh.nc5	1.47	0.04	0.12	1.36	7.7	0	0.99	1.93	0.06	0.56	1.59	5.72	0.26	1
box.cr.kh.v3.exp.nc2	1.51	0.04	0.11	1.13	6.33	0.01	0.99	2.06	0.07	0.6	1.75	5.68	0.04	0.98
box.cr.kh.v3.exp.nc3	1.48	0.03	0.11	1.08	5.34	0	0.99	2.09	0.08	0.63	1.88	5.86	0.04	0.98
box.cr.kh.v3.exp.nc4	1.45	0.03	0.11	1.13	4.99	0	0.99	2.19	0.09	0.66	1.98	5.92	0.18	0.98
box.cr.kh.v3.exp.nc5	1.45	0.03	0.11	1.02	4.89	0.01	0.99	2.37	0.09	0.66	1.75	5.89	0.32	0.98
box.cr.kh.v4.pol.nc2	1.46	0.04	0.12	1.22	6.16	0.01	0.99	1.85	0.06	0.56	1.69	5.41	0.11	0.99
box.cr.kh.v4.pol.nc3	1.45	0.04	0.11	1.21	7.46	0.01	0.99	1.8	0.06	0.54	1.63	5.09	0.01	0.99
box.cr.kh.v4.pol.nc4	1.36	0.03	0.11	1.14	7.13	0.01	0.99	2.07	0.07	0.6	1.7	5.42	0.05	0.99
box.cr.kh.v4.pol.nc5	1.41	0.03	0.11	1.19	6.72	0.01	0.99	1.85	0.06	0.53	1.48	4.95	0.21	0.99
box.cr.kh.v4.sin.nc2	1.49	0.04	0.12	1.33	6.95	0	0.99	1.83	0.06	0.56	1.74	5.82	0.07	0.99
box.cr.kh.v4.sin.nc3	1.49	0.04	0.12	1.28	8.11	0.01	0.99	1.8	0.06	0.54	1.61	5.4	0.01	0.99
box.cr.kh.v4.sin.nc4	1.48	0.04	0.12	1.3	8.65	0.03	0.99	1.79	0.06	0.53	1.55	5.47	0.04	0.99
box.cr.kh.v4.sin.nc5	1.45	0.04	0.12	1.28	7.55	0.01	0.99	1.82	0.06	0.53	1.54	5.47	0.32	0.99
box.cr.kh.v4.tnh.nc2	1.57	0.04	0.13	1.4	7.28	0.01	0.99	1.83	0.07	0.57	1.79	6.04	0.03	0.99
box.cr.kh.v4.tnh.nc3	1.56	0.04	0.13	1.39	8.33	0	0.99	1.84	0.06	0.55	1.63	5.68	0.39	0.99

Table E: continued

cr = cluster wise regression, kh=SOM clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box Gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

Method	training statistics							prediction statistics						
	mn error	ms error	rms error	error std	max error	min error	slope	mn error	ms error	rms error	error std	max error	min error	slope
box.cr.kh.v4.tnh.nc4	1.51	0.04	0.12	1.35	9.01	0	0.99	1.78	0.06	0.54	1.62	5.78	0.04	0.99
box.cr.kh.v4.tnh.nc5	1.47	0.04	0.12	1.36	7.8	0	0.99	1.93	0.06	0.56	1.58	5.69	0.28	1
box.cr.kh.v4.exp.nc2	1.5	0.04	0.11	1.13	6.46	0	0.99	2.06	0.07	0.6	1.75	5.68	0.04	0.98
box.cr.kh.v4.exp.nc3	1.48	0.03	0.11	1.08	5.41	0	0.99	2.09	0.08	0.63	1.87	5.85	0.05	0.98
box.cr.kh.v4.exp.nc4	1.45	0.03	0.11	1.13	5.12	0.01	0.99	2.18	0.09	0.66	1.98	5.87	0.16	0.98
box.cr.kh.v4.exp.nc5	1.44	0.03	0.11	1.02	5	0.02	0.99	2.36	0.09	0.66	1.75	5.9	0.31	0.98
box.cr.kh.v5.pol.nc2	1.33	0.03	0.11	1.14	5.51	0.01	1	1.83	0.06	0.53	1.47	4.69	0.02	1
box.cr.kh.v5.pol.nc3	1.31	0.03	0.11	1.14	6.63	0.01	1	1.69	0.05	0.5	1.48	4.38	0.01	1
box.cr.kh.v5.pol.nc4	1.24	0.03	0.1	1.04	6.3	0.01	1	2.14	0.06	0.56	1.32	4.7	0.13	1
box.cr.kh.v5.pol.nc5	1.3	0.03	0.1	1.09	5.89	0.01	1	1.95	0.05	0.51	1.18	4.22	0.14	1
box.cr.kh.v5.sin.nc2	1.4	0.03	0.11	1.23	6.26	0.02	1	1.85	0.06	0.54	1.55	5.1	0.1	1
box.cr.kh.v5.sin.nc3	1.38	0.03	0.11	1.19	7.28	0	1	1.67	0.05	0.49	1.44	4.67	0.11	1
box.cr.kh.v5.sin.nc4	1.39	0.03	0.11	1.19	7.82	0	1	1.88	0.05	0.51	1.27	4.76	0.32	1
box.cr.kh.v5.sin.nc5	1.35	0.03	0.11	1.18	6.71	0	1	1.92	0.05	0.52	1.33	4.74	0.17	1
box.cr.kh.v5.tnh.nc2	1.51	0.04	0.12	1.28	6.59	0	1	1.85	0.06	0.55	1.62	5.32	0.11	1
box.cr.kh.v5.tnh.nc3	1.49	0.04	0.12	1.27	7.5	0.01	1	1.62	0.05	0.5	1.55	4.96	0.02	1
box.cr.kh.v5.tnh.nc4	1.44	0.04	0.12	1.23	8.18	0	1	1.91	0.05	0.52	1.35	5.07	0.26	1
box.cr.kh.v5.tnh.nc5	1.39	0.03	0.11	1.25	6.97	0.01	1	2.1	0.06	0.56	1.4	4.97	0.05	1
box.cr.kh.v5.exp.nc2	1.36	0.03	0.11	1.08	5.59	0	1	1.77	0.05	0.52	1.51	4.93	0.07	0.99
box.cr.kh.v5.exp.nc3	1.36	0.03	0.1	0.99	4.98	0.01	1	1.77	0.06	0.54	1.65	5.11	0.03	0.99
box.cr.kh.v5.exp.nc4	1.34	0.03	0.1	1.03	5.56	0.01	1	1.94	0.07	0.58	1.69	5.17	0.11	0.99
box.cr.kh.v5.exp.nc5	1.3	0.03	0.1	0.96	5.48	0.04	1	2.12	0.07	0.58	1.47	5.14	0.03	0.99
box.cr.at.v1.pol.nc5	1.17	0.02	0.09	1	6.73	0	1.01	1.16	0.02	0.32	0.84	3.16	0.22	1.01
box.cr.at.v1.sin.nc5	1.15	0.02	0.09	0.94	5.94	0	1.01	1.28	0.02	0.35	0.89	3.43	0	1.01
box.cr.at.v1.tnh.nc5	1.21	0.02	0.09	0.95	6.03	0	1.01	1.38	0.03	0.37	0.89	3.52	0.06	1.01
box.cr.at.v1.exp.nc5	1.1	0.02	0.09	0.95	5.45	0.01	1	1.4	0.04	0.44	1.39	4.62	0.09	1.01
box.cr.at.v2.pol.nc5	1.31	0.03	0.1	1.04	6.77	0	1.01	1.38	0.03	0.37	0.93	3.46	0.07	1.01
box.cr.at.v2.sin.nc5	1.3	0.03	0.1	0.99	6.06	0.01	1.01	1.6	0.03	0.41	0.89	3.73	0.3	1.02
box.cr.at.v2.tnh.nc5	1.35	0.03	0.1	1	6.15	0.01	1.01	1.72	0.04	0.43	0.91	3.83	0.13	1.02
box.cr.at.v2.exp.nc5	1.22	0.03	0.1	1.02	5.42	0.01	1.01	1.46	0.04	0.45	1.42	4.78	0.2	1.01
box.cr.at.v3.pol.nc5	0.86	0.01	0.06	0.57	4.7	0	0.99	0.87	0.01	0.23	0.58	2.21	0.01	0.99
box.cr.at.v3.sin.nc5	0.9	0.01	0.07	0.7	4.95	0	0.99	0.71	0.01	0.2	0.56	2.1	0.01	0.99
box.cr.at.v3.tnh.nc5	0.96	0.02	0.08	0.82	4.94	0	0.99	0.68	0.01	0.2	0.57	2.39	0.15	1
box.cr.at.v3.exp.nc5	1.02	0.01	0.07	0.65	3.7	0	0.99	1.13	0.02	0.29	0.6	2.66	0.24	0.99

Table E: continued

cr = cluster wise regression, kh=SOM clustering, at=A.R.T.2 clustering, v1,v2,v3,v4,v5 = variation 1, 2,3,4,5 pol,sin,tnh,exp = polynomial,sin,tan hyperbolic exponential modeling functions, nc = no. clusters,box=model of Box Gas Furnace mn error = mean error, ms error = mean squared error rms error = root mean squared error, error std = standard deviation of error, max error = maximum error, min error = minimum error

	training statistics						prediction statistics				
problem	mn error	rms error	max error	min error	slope		mn error	rms error	max error	min error	slope
box	0.54	0.04	0.48	3.01	0.99		0.55	0.41	0.78	0.32	1
ica	2.1	3.4	4.9	0.21	1.01		3.8	3.1	3.12	0.6	0.99
pca	2.9	2.1	5.23	1.2	1.01		3.32	4.4	6.32	0.85	1.01
rd	1.8	0.68	6.7	0.03	1		7.48	6.45	9.23	2.1	0.93
md	3.1	3.78	7.8	0.11	0.99		7.8	9.1	13.1	0.89	1.08

Table 3.1 evaluation of Sugeno method on each problem

mn error = mean error, ms error = mean squared error, rms error = root mean squared error, error std = standard deviation of er
max error = maximum error, min error = minimum error box = Box Jenkins' gas furnace modeling
ica, pca, rd, md =estimation of life of converter lining problem (ICA), (PCA), (mean, R&D) and (median, R&D)

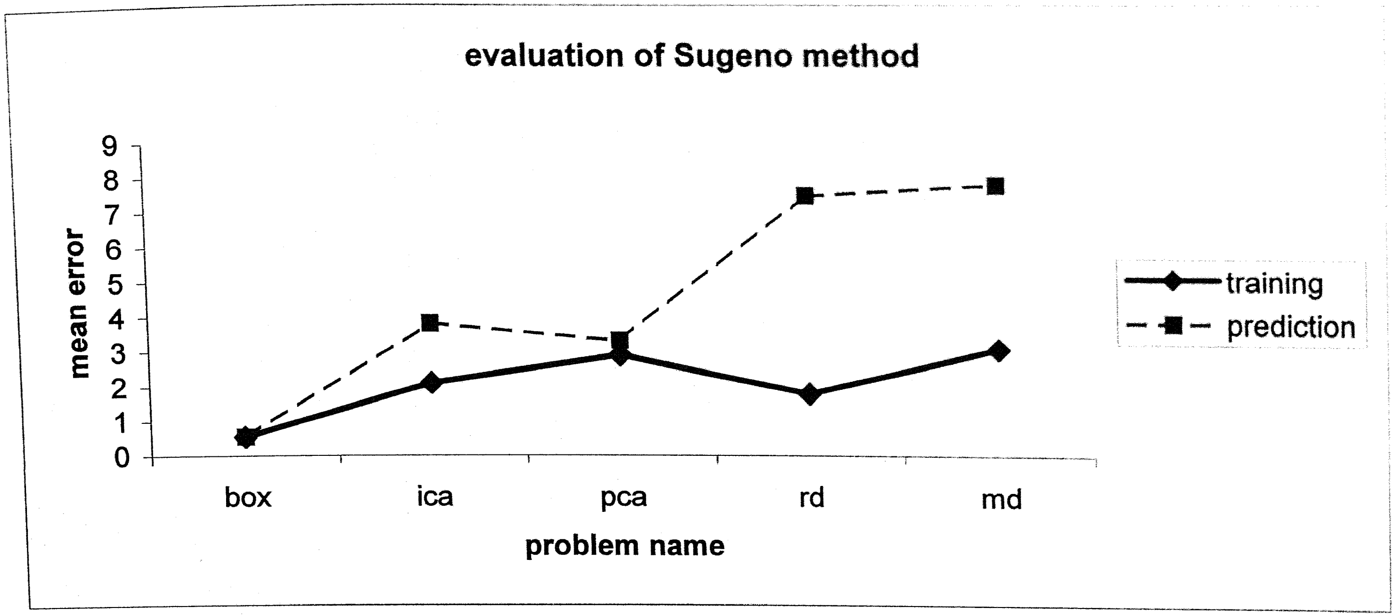

Fig 3.1 evaluation of Sugeno method on each problem